دهمین کنفرانس بین المللی مدیریت پروژه
10th International Project Management Conference

Controlling EVM indices in construction projects by a statistical technique

Fatemeh Sogandi [1], S. Meysam Mousavi [2], Amirhossein Amiri [2]

M.Sc. Student, Industrial Engineering Department, Faculty of Engineering, Shahed University, Tehran, Iran, f.sogandi@shahed.ac.ir
Assistant Professor, Industrial Engineering Department, Faculty of Engineering, Shahed University, Tehran, Iran

Abstract:

Earned Value Management (EVM) is considered as a well-known approach in project control system. Although the EVM indicators are the most effective tools in the measurement of project cost and schedule performance, they cannot show continual performance variations. Considering the EVM indices, Statistical Process Control (SPC) methods can monitor variation of project performances persistently, and they lead to improve substantially project controlling scheme. In this paper, a self-starting monitoring using multivariate control chart is applied in the analysis of earn value indices owing to costly sampling and lack of historical data in the projects. Also, these indices are assumed auto-correlated to enhance more applicability in real cases. In addition, usually EVM indices are distributed non-Normal in practice. For this end, auto-correlated earn value indices are monitored with considering correlation between them in which indices can be distributed non-Normal. So, a Mont Carlo simulation study is done regarding the probability of the signal criterion. Finally, the performance of the proposed approach is shown through an illustrative example.

Keywords: Correlated schedule and cost performance indices; Self-starting monitoring; Auto-correlated non-Normal EVM indices.

1. Introduction

The earned value management helps project managers to have an integrated monitoring time and cost to be performed in conformity with project scope. In fact, the EVM is considered as an effectual tool to measure project performance and progress in terms of cost deviation and schedule deviation and estimate actual time and cost at completion. Often, in project management two performance indices, called as Schedule Performance Index (SPI) and Cost Performance Index (CPI), are taken in order to conduct project on time and budget with desirable quality. The schedule and cost performance indices can be computed by dividing Earned Value (EV) on Planned Value (PV) and Actual Cost (AC), respectively. According to mentioned definition, it is expectable if they would be equal to 1 or higher than 1, it means that project performance is suitable and consequently the project will be finished on planned time and cost or with less required time and budget in comparison with planned values. In contrast, when SPI and CPI indexes would be smaller than 1, needing budget or duration is more than planned values, and project state is not favorable. In these situations, corrective

actions should be conducted to refine the project more than before in order to achieve project goals effectively.

Several studies have been done on the EVM indices applications. One of the earliest work goes back to Lipke [1]. After that, Blonco [2] and Burke [3] showed that implementing EVM indices can be effectively contribute on improvement of the project monitoring. Henderson [4, 5] declared that earned schedule has become a dimension to integrate technical performance measurement with earned value management. Also, the study developed earned schedule index such that Historic EVM cost based indices and duration based earned schedule indicators would be equivalent. In addition, Fleming and Coppelman [6] introduced the in EV-project management indices as a powerful tool for software projects. Formalism was proposed with scientific notation for EVM indices by Cioffi [7]. Moreover, Naeni and Salehipour [8] presented an approach to deal with fuzzy earned value indices. Pajares and Paredes [9] extended the EVM analysis for project monitoring as the cost control index and the schedule control index. Recently, Asebec et al. [10] defined control indexes and cumulative buffers to know when a project deviates from planed values during the project lifecycle. The schedule performance indices are optimized via introducing schedule performance and the weight value by Zheng and Bi [11]. Chen [12] suggested an approach to increasing the prediction accuracy of EV and AC value.

Although schedule and cost performance indices measure project progress exactly, they cannot report accepted level of time and cost deviations from their plan. So, providing control mechanism of earned value metrics is essential to monitor persistent projects progress over time. In this respect, Statistical Process Control (SPC) techniques are utilized as effectual tools to monitor and manage project performance continual so that additional changes of in-progress project cost and schedule trends can be shown timely. There are some related studies which have been carried out in applying SPC techniques in analysis of EVM indices. Lipke and Vaughn [13] applied individuals and moving Range (ImR) charts and computed the control limits considering normality assumption of the EVM indices. Bauch and Chung [14] used the control charts for EVM and evaluated single observations relative to historical project data from 20 similar projects. Anbari [15] presented a control chart named target performance chart to evaluate EVM indexes and consequently Critical Ration index. Wang et al. [16] utilized the control charts in the EVM indices on a set of more than 30 software projects with non-Normal EVM indexes. Leu et al. [17] presented quantitative procedure for monitoring and evaluating project performance indices. After that, Leu and Lin [18] improved the EVM indices performance by implementing individual control charts, and provided a log transformation method for the SPI and CPI indexes in which control limits were calculated from historical data of 120 projects performed by a management consulting company. Noori et al. [19] applied fuzzy control chart in EVM analysis. In addition, Naeni et al. [20] extended fuzzy control charts to monitor the EVM indexes, and provided a transformation method based on fuzzified indexes. Lipke et al. [21] improved the capability of project managers for making decisions by providing a valid estimating method of the completion cost and duration. As a recent work, Aliverdi et al.[22] applied ImR charts to monitor earned value indexes. Colin and Vanhoucke [23] proposed a SPC procedure sets tolerance limits to improve detection power between progresses situations that were probably occur under the project baseline schedule. Moreover, proposed approach that will be provided in next sections given to compare with other studies.

Usually related works analyzed EVM indices indecently, while it is obvious that they have a strong correlation in real world. Also, they should be assumed auto-correlated to enhance more method applicability. The most studies assumed the EVM indices are distributed normal to allow using Showhart control charts. As a result, in this paper independence and normality assumption are discarded as well as auto-correlation considered for any indexes. Moreover, a self-starting monitoring is applied in monitoring EVM indices due to costly sampling and lack of data in projects.

The structure of the paper is as follows: the next section 2 explains a new technique in modifying assumptions. In section 3, proposed technique for monitoring EVM indexes is elaborated. Section 4 shows a performance evaluation to appraise our methodology, and section 5 provides an illustrative example. Finally, conclusions and some recommendations for future studies are provided.

2. Proposed technique

Based on aforementioned explanation, EVM techniques are used for measuring project performance and progress. Analysis of in-progress project cost and schedule performance indexes are the most important issue for the success of project. Combining the use of a control chart with the EVM indices allows project teams to monitor persistently the variation of the performance indexes over time because the EVM indices provide a snapshot of performance at a given time. So, applying the SPC tools in EVM leads to reduce project using timely correction action. Here, we integrate EVM with the SPC techniques to decrease complexity of management judgment project state. In this regard, firstly it is necessity to modify the assumptions in order to provide real aspect to proposed approach. Usually, based on underlying assumptions in applying control charts, samples should be normally and identically distributed as well as they should be statistically independent of each other (i.e., an samples should not affect other samples).

In scope of analysis of EVM indices, Lipke [24] also argued that if the assumption of Normal distribution is not satisfied, the analysis of control charts may be affected. Thereafter, Lipke [25] used logarithms transforms the EVM indices in eight projects to estimate a normal distribution. Of course, in these situations, the EVM application was mainly labor only. So, the data with non-normal distribution generally need to be transformed to the normal distribution. In this section, Normal To Anything (NORTA) inverse method is used to transform EVM indices with any distribution to normal. The readers can see Niaki and Abbasi [26] for details. Monitoring the EVM indicators that taken together provides very perfect information for the analysis of project performance. It should be noted that cost performance is strongly correlated with the time performance of the activity. Hence, it is assumed correlation between EVM indexes. On the other hand, it is obvious that both of the EVM indices (i.e., SPI and CPI indexes) have nature auto-correlative during the time. In other words, these indexes are affected by previous indexes. One simple approach of describing structure of the auto-correlative EVM indexes is time series model. Note that, control charts should be applied to the residuals in order to remove the autocorrelation from the EVM indices. Here, for the sake of computation simplicity, it is assumed that the auto-correlative indices are come from an multivariate first-order autoregressive MAR(1) model with the following definition:

$$\mathbf{x_t} = \Sigma \mathbf{x_{t\text{-}1}} + \mathbf{e_t}, \tag{1}$$

where $\mathbf{x_t} = (SPI_t, CPI_t)$, the residual vector is equal to $\mathbf{e_t} = (e_{SPI,t}, e_{CPI,t})$ and variance covariance matrix of the EVM indices is $\mathbf{\Sigma} = \begin{bmatrix} \sigma_{SPI}^2 & \rho\sigma_{SPI}\sigma_{CPI} \\ \rho\sigma_{SPI}\sigma_{CPI} & \sigma_{CPI}^2 \end{bmatrix}$ in which ρ is correlation between indexes ($-1 \le \rho \le 1$). To summarize proposed approach, firstly an overall scheme of the framework monitoring schedule and cost performance indices is presented in Fig.1.

3. Proposed procedure of the monitoring approach

As mentioned before, the SPC-based EVM leads to efficiently inform project managers on performance indexes trend and magnitude of their variations during the project progress. In this section, a quantitative procedure for evaluating project performance indexes is provided in detail. It can be understood from Fig. 1 that the proposed approach enhances method applicability and validity using modification assumption data. In other words, project performance indexes are assumed auto-correlative and distributed non-normal. Also, correlation between indices is considered. For this purpose, a self-starting monitoring using multivariate control chart is utilized with considering given characters of projects such as unique and short run time.

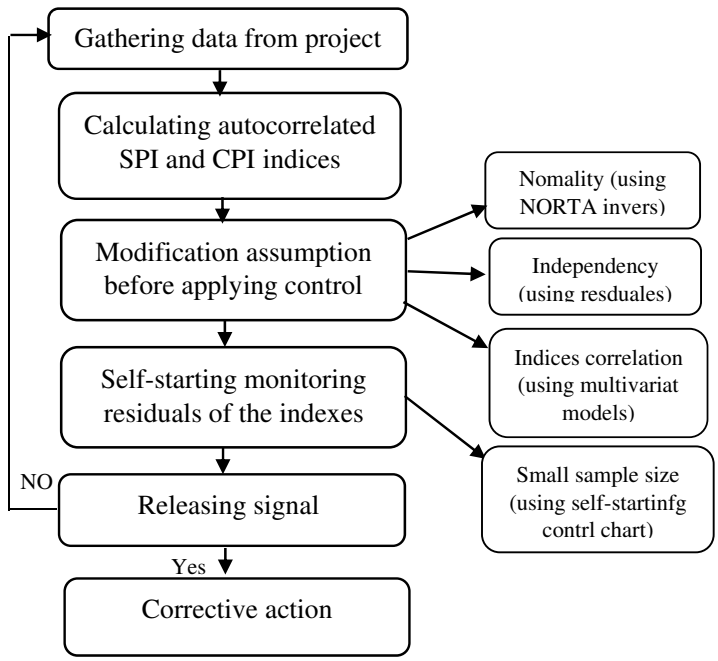

Fig. 1. Flowchart of the proposed approach for monitoring EVM indices

Classic control charts are often applied by assuming that process parameters are known or may be estimated using large Phase I samples collected before a production run. However, in monitoring of projects performance indices, there are not historical data to exactly estimate the in-control process parameters because projects are not repetitive. In addition, it cannot be collected large sample during project progress due to lack of data in life cycle time. Note that large samplesleads to the estimates will be close to the true measurements. In these situations, the self-starting control chart outperform traditional control charts which uses consecutive samples to update the EVM indices estimates. So, we initiate using a self-starting control chart to monitor EVM indices among different phases of the project. In this regard, we have applied a self-starting statistic proposed by Quesenberry [27] called as Q statistic according to equation (2).

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

where r is the number of project performance indices, $\mathbf{x_r}$ and $\mathbf{s_r}$ are the indices mean vector and the indices standard deviation, respectively, Φ^{-1} denotes the inverse of the standard normal distribution function, and G_{r-2} is the student's t distribution function with r-2 degrees of freedom. Here, we use the residuals of a time series model MAR(1) for performance indices in conjunction with the Q statistics. These self-starting charts begin controlling the EVM indices without the need for early indexes. In fact, the self-starting chart utilizes the deviation of each project performance index vector from the average of all previous indices and allows immediately to start effectual control EVM indices. Hence, applying the Q statistic with unknown process parameters to these residuals gives independent standard Normal variables. As a result, this statistic can be plotted on a well-known multivariate control chart named as T^2 chart according the following equation.

$$T_r^2 = (\mathbf{Q_r} - \overline{\mathbf{Q}})\Sigma_{\mathbf{Q}}^{\mathbf{-1}}(\mathbf{Q_r} - \overline{\mathbf{Q}}),\ r=3, 4, \ldots \tag{3}$$

in which $\bar{\mathbf{Q}}$ and $\mathbf{\Sigma_Q}$ denotes mean vector and covariance variance matrix of the Q statistic. The Upper Control Limit (UCL) of the T_I^2 control chart is determined by simulation such that a desired in-control Average Run Length (ARL) is obtained. The project performance indices would deviate more than expected values would be out-of-control when one statistic exceeds the UCL**.**

4. Performance evaluation

In this section, a simulation with 10000 replications is used to evaluate performance of the proposed approach using well-known criteria. The Monte Carlo simulation is utilized to increase validity of the proposed prosedure in monitoring of the EVM indices under uncertaity condition. For this purpose, it is assumed that the schedule and cost performance indices are generated from a uniform distribution with parameters (0.5,1.5) and (0.4,1.3), respectively. In our simulation, these indexes are generated according to time series model MAR(1) in which ρ is equal to 0.375. Note that, considering autocorrelative data result in more applicability proposed procedure in real world. As aformentioned, the residuals of the time series model are monitored instead of recessive project performance indexes in order that control charts accurately alarm among different phases of the project. Then, we import related resedules to $\mathbf{Q_r}$ (r=3,4, …) statistic mentioned in equation (2) in order to monitor project performance indexes. Recall from the previous section, the $\mathbf{Q_r}$ statistic updates the parameter estimates with each new sample and simultaneously control project condition viewpoint of cost and schadule performance. The self-starting chart begins controlling the process without the need for preliminary EVM indices. So, we have applied $\mathbf{Q_r}$ statistic on the T^2 hotelling chart to monitor project progress without need to large sample size or historical data. The $\bar{\mathbf{Q}}$ and $\mathbf{\Sigma_Q^{-1}}$ in T^2 hotelling can be obtained with 10000 simulation runs such that they are calculated based on previous statistics. In this simulation study, they are computed as follow:

$$\bar{\mathbf{Q}} = [0.0155, -0.0110],\ \mathbf{\Sigma_Q^{-1}} = \begin{bmatrix} 1.0350 & 0.3676 \\ 0.3676 & 1.0720 \end{bmatrix}.$$

On the other hand, T^2 hotelling chart account for the correlation structure of the SPI and CPI indexes, in consequence these charts can show an apparently perspective of the overall project performance indexes. In this regard, a simulation study is done regarding the probability of the signal criterion. In other words, the proposed approach performance in detection of the shift in index(es) is measured in terms of Average Run Length (ARL) criterion. The ARL is the average of the number of samples which should occur before a sample shows the out-of-control condition for the project. when the project is in the state of in-control, ARL is shown by $ARL_0 = \frac{1}{\alpha}$ .The ARL_0 denotes the number of samples' average which should occur before a control chart alarms under type I error equal to α . In contrast, when the project is out-of-control, $ARL_1 = \frac{1}{1-\beta}$ is the number of samples which take place until a control chart alarms where β is the type II error and shows the mistake probability of detection a shift with the first point after the occurrence of a shift in the project performance indexes. In EVM indices monitoring, firstly the UCL is fixed to obtain error type I (α) equal to 0.05. Hence, the UCL is simulated equal to 5.88 with 10000 replication such that predetermined α is obtained. Then, the $\mathbf{Q_r}$ statistic is generated until exeed from the UCL. We denote the magnitude of shifts in the EVM indices mean by δ in 30th period, and then obtain ARL_1 under different step shifts separately or simultaneously. As a result, simulation results are shown in Table 1.

Table 1. Performance of the methodology under different shift in EVM indices mean interms of ARL_1

δ	Shift in SPI index mean	Shift in CPI index mean	Simotaneusly shift indices
0.01	50.68	52.15	50.21
0.02	49.47	50.14	49.02
0.05	47.85	46.59	45.11
0.1	47.21	46.33	43.97
0.12	47.03	45.95	42.88
0.15	46.61	45.11	41.52
0.2	44.02	44.97	41.3

It should be noted that the lower ARL_1 leads to more power control charts in shift detection. So, as shown in the Table 1, the proposed procedure outperform in monitoring project cost and scheduling performnace indexes under different shifts. According to our expectance, as the magnitude of the step shift in EVM indices increases, the detection power of shift using applied control chart enhances signaficantly. At last, it can be concluded that autocorrelated cost and schadule performance indexes coming from time serie model are simultaneously monitored using this methodology. By comparison between different states of the shifts in the EVM indices (separately and simolataneusly), it can be concluded that proposed technique have more power of detection in the simultaneously shifts against other states.

5. Illustrative example

To illustrate the application of the proposed technique in monitoring EVM indices, we provide an illustrative example. In this respect, mentioned notations in previous section is used. In addition, it is considered a shift with magnitude of δ =0.02 in 20th period for the cost performance index as efficiency of the cost used on the project. It means that project exceed its allocated cost because the CPI is calculated as the measure of the value of work completed compared to the actual cost or progress made on the project. So, project managers strive for improvement of the project progress using triggered signals from control chart. Figure (2) demonstrates T^2 hoteling constructing from **Q** statistic.

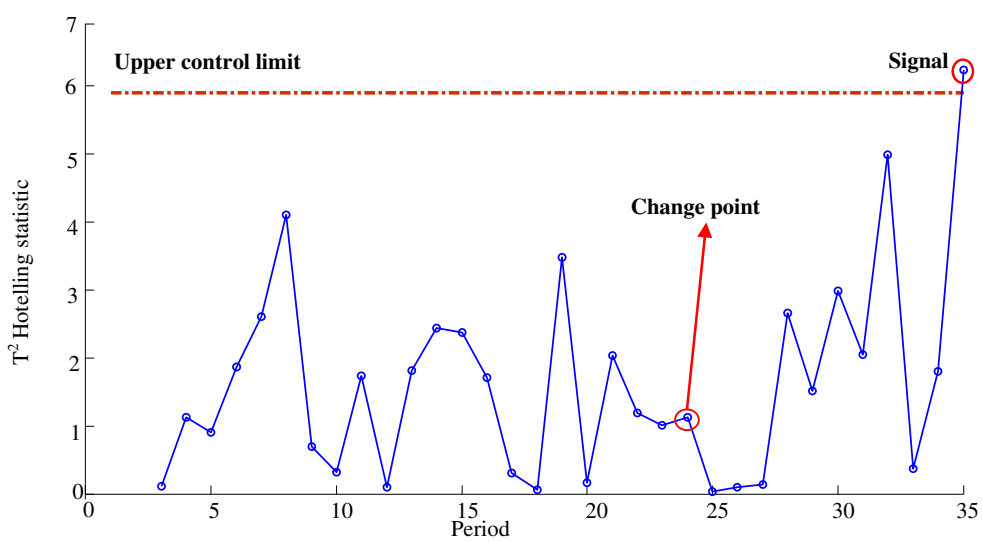

Fig. 2. Simultaneously monitoring EVM indices

6. Conclusion

EVM indexes can not represent information about trend and variation of the project performance during the project lifecycle.This paper mainly applied the applicable tools of the SPC and adopted the concept of SPC with EVM to analyze project performance indexes. So, a self-starting monitoring using multivariate control chart was proposed in monitoring earned value indices due to costly sampling and lack of data in projects. Also, the SPI and CPI indices can be allowed correlated and distributed non-normal with considering their practicality aspects as well as they were assumed correlated. Therefore, a simulation study was conducted regarding the probability of the signal criterion. Results showed that the proposed technique could handle the project progress and distinguish the out-of-control conditions for cost and schedule performance indexes. So, it was concluded that the proposed technique for monitoring EVM indexes enhanced considerably the project controlling scheme.

References

[1] Lipke, W., Applying management reserve to software project management, Journal of Defense Software Engineering, 1999, pp:17–21.
[2] Blanco, V.D., Earned value management: a predictive analysis tool, Navy Supply Corps Newsletter, 66 (2), 2003, pp:24–27.
[3] Burke, R., Project management planning and control techniques, 4th ed. 2003.
[4] Henderson, K., Earned schedule: a breakthrough extension to earned value theory? A retrospective analysis of real project data, The Measurable News, 2003, pp:13–23.
[5] Henderson, K., Further developments in earned schedule, The Measurable News, 2004, pp:15–22.
[6] Fleming, Q.W., Koppelman, J.M., Earned value project management, 3th ed. Project Management Institute. 2005.
[7] Cioffi, D.F., Designing project management: a scientific notation and an improved formalism for earned value calculations. International Journal of Project Management 24, 2006, pp:136–144.
[8] Naeni, L.M., and Salehipour, A., Evaluating fuzzy earned value indices and estimates by applying alpha cuts, Expert systems with Applications, 38(7), 2011, 8193-8198.
[9] Pajares, J., and Lopez-Paredes, A., An extension of the EVM analysis for project monitoring: the cost control index and the schedule control index, International Journal of Project Management, 29 (5), 2011, 615-621.
[10] Acebes, F., Pajares, J., Galán, J. M., and López-Paredes, A., Beyond earned value management: A graphical framework for integrated cost, schedule and risk monitoring. Procedia-Social and Behavioral Sciences, 74, 2013, pp:181-189.
[11] Zheng, Q.B., and Bi, X., Optimization on earned value method combined with critical path. In Proceedings of 2013 4th International Asia Conference on Industrial Engineering and Management Innovation (IEMI2013) Springer Berlin Heidelberg, pp:707-715.
[12] Chen, H.L., Improving forecasting accuracy of project earned value metrics: linear modeling approach. Journal of Management in Engineering, 30(2), 2014, 135-145.
[13] Lipke, W., Vaughn, J., Statistical process control meets earned value, CrossTalk: The Journal of Defense Software Engineering June, 2000, 13 (6), pp: 16–20.
[14] Bauch, G.T. and Chung, C.A., A statistical project control tool for engineering managers, Project Management Journal 32, 2001, pp:37–44.
[15] Anbari, F.T., Earned value project management method and extensions, International Journal of Project Management, 34 (4), 2003, pp:12–23.
[16] Wang, Q., Jiang, N., Gou, L., Che, M., and Zhang, R., Practical experiences of cost/schedule measure through earned value management and statistical process control. Software Process Change. Springer Berlin Heidelberg, 2006. pp:348-354.
[17] Leu, S.S., Lin, Y.C., Chen, T.A., and Ho, Y.Y., Improving traditional earned value management by incorporating statistical process charts, Proceedings of ISARC, 2006, 275-280.

[18] Leu, S.S. and Lin, Y.C., Project performance evaluation based on statistical process control techniques, Journal of Construction Engineering and Management 134, 2008, pp:813–819.

[19] Noori, S., Bagherpour, M., and Zareei, A., Applying fuzzy control chart in earned value analysis: a new application. World Applied Sciences Journal, 3(4), 2008, 684-690.

[20] Naeni, L.M., Shahram Sh., and Salehipour A., A fuzzy approach for the earned value management. International Journal of Project Management, 29 (6), 2011, pp:764-772.

[21] Lipke, W., Zwikael, O., Henderson, K., and Anbari, F., Prediction of project outcome: The application of statistical methods to earned value management and earned schedule performance indexes, International Journal of Project Management, 27(4), 2009, 400-407.

[22] Aliverdi, R., Naeni, L.M., and Salehipour, A., Monitoring project duration and cost in a construction project by applying statistical quality control charts, International Journal of Project Management, 31 (3), 2013, pp:411-423.

[23] Colin, J. and Vanhoucke, M., Setting tolerance limits for statistical project control using earned value management. Omega, 49, 2014, 107-122.

[24] Lipke, W., A study of the normality of earned value management indicators, The Measurable News 4, 2002, pp:1-16.

[25] Lipke, W., Further study of the Normality of CPI and SPI (t), PM World Today XIII (X), 2011.

[26] Niaki, S.T.A. and Abbasi, B., Generating correlation matrices for normal random vectors in NORTA algorithm using artificial neural networks, Journal of Uncertainty System, 2, 2008, pp:192–201.

[27]Quesenberry, C.P., SPC Q chart for start up processes and short or long runs,Journal of Quality and Technology, 23, 1991, pp:213-224.

[28] Nedumaran, G., Pignatiello Jr, J. J., and Calvin, J. A., Identifying the time of a step-change with $\chi 2$ control charts,Quality Engineering, 13(2), 2000, pp:153-159.

[29] Runger, G.C., Alt, F.B., and D.C., Montgomery, Controlling multiple stream processes with principal components, International Journal of Production Research, 34 (11), 1996, pp: 2991–2999.