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Using of Statistical Process Control for Performing Quality Control in Construction Projects

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ABSTRACT

One of the distinguished procedures that can be used to perform quality control of the products is through the Statistical Process Control (SPC).This paper uses multivariate control chart Cumulative Sum based on Projection Pursuit (PPCUSUM) to recognize a shift in the procedure when the direction of the shift is not limited.It was useful to observe the production process of OPC (Ordinary Portland Cement). Four feature qualities of OPCwhich entails of free lime, SO3, CaO, and mesh were used to determine whether the production of the cement is undercontrolof quality. The PPCUSUM control diagram shown that by using (h) = 12.3294 as the control limit, the first sample that exceeded the edge is sample number 10 but when the control limit standards (h) =h = 13.7009 and h = 18.0027 were applied; the first sample that is out of control is sample number16.Besides that, once the first sample was revealed to be out of the control limit, the PPCUSUM control chart can recognize the exact time of when the production procedure became out of control in this revision. Even though it was revealed that sample number 16 is the first sample to be out of control, the precise time at which the process shift has happened was discovered earlier in sample number 8. Themediocre optimal shift for adjustable namely the free lime, SO3, CaO and mesh is (0.962416; 0.235219; 0.125824; 0.05094).

***Keywords**:Optimal control, Management of production, Standards of best product.*

INTRODUCTION

The Statistical Control Chart is one of the most powerful tools in quality control. First developed in the 1920's by Walter Shewhart, the control chart found wide spread use during the World War II and has been employed with various modifications (Jackson, 1985). There are many factors that influenced the development of quality control. One of them is the rapid growth of the data; not only in quantity, but also in the type as well as the variables involved in one case. Advanced analyses and technology are needed in monitoring the production process for a case with more than one quality characteristics. The techniques are often referred to as the multivariate statistical process control procedures [1].

Cumulative Sum (CUSUM) control chart is widely used in the industrial sectors due to its effective nature in detecting shifts in process control, particularly in those areas where a tighter process control is needed, as compared to other charts. It works by accumulating a recent process data in detecting out of control situations. A signal from CUSUM chart does not mean that there are failures in the production process, but rather, it raises an alarm for necessary action to be taken to make sure the production process still under control [2].

In industrial zones nowadays, there are many situations that necessitate simultaneous monitoring of two or more related quality process characteristics. Monitoring these quality characteristicsindependentlycan be misleading. Therefore in order to avoid mistakes in performing quality control, simultaneous observation is needed in a process that involves many variables. There are many researchers working on control procedures with more than one variable (multivariate). Three most accepted multivariate quality control include the Hostelling T^2 , Multivariate Exponential Weighted Moving Average (MEWMA) and Multivariate Cumulative Sum (MCUSUM) [3].

Multivariate process control techniques were established by Hotelling in 1947. Hotelling appliedT^2 Chart to a bombsights problem. It is well known that the T^2chart is reliable in detecting the big shift from production process. However, it is relatively insensitive in detecting moderate and small shifts. HostellingT^2 is less sensitive to small shifts in the mean vector as compared to MCUSUM and MEWMA chart due to the fact thatT^2chart use information from current samples. This weakness raise problems on how to build the two sided CUSUM and EWMA chart as a multivariate counterpart for T^2 control chart [4].

Multivariate EWMA (MEWMA) control chart was introduced by Lowry *et.al.*, (1992). MEWMA control chart is developd from EWMA control chart. Inertia happens in MEWMA control chart, just as it does in EWMA control chart. Inertia is a condition when there is a plotted statistic on one side of the centre line with a shift towards the other side of center line which indicates a closer observation until the control chart give a shift signal [5]. There are some improvements in MEWMA. Kramer and Schmid (Kramer and Schmid, 1997) suggested a generalization of the MEWMA control scheme by Lowry *et al.* (1992) for a multivariate time dependent observation. Sullivan and Woodall (1998) recommended the use of MEWMA for preliminary analysis of multivariate observations. Fasso (1999) developed a one sided MEWMA control chart based on the restricted Maximum Likelihood Estimator. All of the previous works above resulted in a better MEWMA control chart with minimum inertia problem and shorter Average Run Length (ARL). ARL is the common tool in measuring time taken for a control chart in detecting a shift in production process [6].

There are three most popular controls in Multivariate Cumulative Sum (MCUSUM). Crosier (1988) developed MCr; while Pignatiello and Runger (1990) developed MC1 and MC2. However, none of those three charts is a natural extension of univariate CUSUM chart. MCUSUM control chart is a control chart with the procedure using the sum of previous observations of random vectors being compared with a nominal value vector that is used to observe the average of multivariate process (Alves *et.al.*, 2010). MCUSUM which was developed by Pignatiello and Runger (1990) make a direct use of the covariance matrix. The difference between MC1 and MC2 is that MC1 accumulates the *X* vector before producing the quadratic forms while MC2 guess the quadratic form each *X*, and then accumulates the quadratic forms [7].

Another research comparing MCr, MC1 and MEWMA was already conducted by Lowry *et.al.* (1992) and it was found that MEWMA, MCUSUM and MC1 control charts preserve a shorter ARL; which means that these charts are reliable in detecting small shifts. However, some of these charts do present a significant amount of inertia. Large amount of inertia indicates that there may be a delayed detection of shifts in the production process. Therefore, Ngai and Zhang (2001)introduced the PPCUSUM control chart as a natural development of CUSUM control chart approach to projection pursuit.The PPCUSUM chart can detect at an earlier stage of any shift occurring in a process that has been under control, as compared to

MC1 and MEWMA charts and also relatively easy to detect when the shift happened. The MC1 and MCrcontrol charts have the advantage in detecting small shifts as compared to PPCUSUM control chart. On the downside, significant amount inertia is present in both of these charts. The large amount of inertia affects the time taken to detect any shift in the process. Multivariate CUSUM control chart approaching to projection pursuit have a smaller amount of inertia than in MC1 and MCr control charts [8].

The differences of products produced in the production process can not be eliminated, however, it can be controlled. The use of multivariate control charts requires products that posses two or more quality characteristics which are interconnected; and require simultaneous control chart (Montgomery, 1996) [9]. The use of Multivariate Control Chart such as the MEWMA, MCUSUM and T^2 control charts are very popular in clinical setting (Waterhouse et.al., 2010).Meanwhile, Retrospective $T^2$is used for automotive stamped parts (Talib *et.al*, 2014); Multivariate Shewhart control chart for controlling the False Discovery Rate (Park and Jun, 2012); HostellingT^2 control chart for maintaining the inside diameter of a steel cylinder (Henning *et.al.*, 2014); and Generalized Variance Chart is applied for multivariate quality control (Hamed, 2014). From the best our knowledge, in the application of multivariate control chart, MCUSUM control chart especially in MCUSUM approach to Projection Pursuit is less popular. Therefore, the objective of this study is to apply statistical quality control of products using multivariate control chart CUSUM approach to projection pursuit committed against products that have more than one quality characteristics. In this paper, we applied the method into four characteristic qualities on the data types of OPC cement, namely thefree lime, SO3, CaO and Mesh [10].

METHODOLOGY

Method Investigation

The investigation of this article is divided into 2 stages. For the first step, the preliminary examination is on the correlation and distribution. The correlation indicates the level or the size of the closeness of the linear relationship between variables X1 and X2. Population correlation coefficient is denoted by ρ is defined as follows (Gujarati, 2004):

$$\rho = \frac{Cov\ (X_1,X_2)}{\sqrt{Var\ (X_1)Var\ (X_2)}} \tag{1}$$

The scale to determine the relationship between the two variables is$-1 \leq \rho \leq 1$. If ρ = 0, then there is no correlation between these variables, or so-called free. Or else, if $\rho \neq 0$ then, there is a correlation between these variables.

Multivariate normal distribution is formed by a normal distribution with a univariate $p \geq 2$ dimension where$p$ is a number of variables or the number of dimensions of quality characteristics. Multivariate odds density function for the vector y is (Rencher, 2002) [11]:

$$f(y) = \frac{1}{(\sqrt{2\pi})^p |\boldsymbol{\Sigma}|^{\frac{1}{2}}} e^{-(\mathbf{y}-\boldsymbol{\mu})^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}(\mathbf{y}-\boldsymbol{\mu})/2} \tag{2}$$

In this equation, $\boldsymbol{\mu}$is a vector with an average sized px1 and $\boldsymbol{\Sigma}$ is the variance-covariance matrix ofsize pxp. Random vector $\boldsymbol{y}$ are normally distributed p-variateand can be written as$\boldsymbol{y} \sim N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$.

Chi-square quantile plots, which are derived from the square of the distance, or also identified as the Mahalanobis distance; can be used to verify whether the data set has a multivariate normal distribution. The data is of multivariate normal if the figure of practical quantiles in opposition to quantiles of the reference distribution will plot as a straight line [12]. Mahalanobis distance can be calculated as follows [13]:

$$d_i^2 = (\boldsymbol{y}_i - \overline{\boldsymbol{\mu}})\boldsymbol{S}^{-1}(\boldsymbol{y}_i - \overline{\boldsymbol{\mu}}) \tag{3}$$

Additionally, to build PPCUSUM control chart, it is obligatory to estimatethe values for $\boldsymbol{\mu}_0$, $\boldsymbol{\Sigma}_0$ and$\boldsymbol{\Sigma}_0^{-1/2}$. To obtain the value of$\boldsymbol{\mu}_0$, $\overline{\overline{\boldsymbol{x}}}$can be used. The variance-covariance matrices $\boldsymbol{\Sigma}_0$ can be approximated by using$\boldsymbol{S}$.

The first investigation in the stage two is done to acquire the value of theAverage Run Length (ARL). ARL is the widespreadtool in measuring how fast of a control chart for the shifting in production process. There are several procedures to find the ARL value, such as method planned by Woodall and Adams (1993) by means of the Sigmund rough calculation due to its simplicity. The rough calculation by Sigmund for ARL_0 is as follows [14]:

$$\boldsymbol{ARL_0} = \frac{\boldsymbol{exp(2k(h+1.166)) - 2k(h+1.166) - 1}}{\boldsymbol{2k^2}} \tag{4}$$

In the case with a value of $k = {}^1/_2$:

$$ARL_0 = 2(e^a - a - 1) \tag{5}$$

The rough calculation of ARL_0 value can be calculated by Monte Carlo simulation with the substitution of *k*-value into the equation of Sigmund rough calculation. PPCUSUM control chart has a reference value (*k*) which is usually predetermined. The value of $k/\sqrt{n}$is about half the mahalanobis distance, where$\mu_0$is an average value of training data when the process is considered to be under control while $\mu_1$is the average value of data testing [15].

$$d(\mu_1, \mu_0) = ((\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)^T \Sigma_0^{-1}((\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0))^{\frac{1}{2}} \tag{6}$$

In CUSUM control chart, the value of *k*relies on the magnitude of the distance μ_1 andμ_0. Consequently, it advanced the control chart's ability through the selection of an alternative *k* value. Based on Ngai and Zhang (2001), PPCUSUM control chart is proportionally easy to apply and have a better performance when comparedto the MC1control chart [16]. To make an investigation easier, standardizationneed to be done with the equationlike this:

$$\overline{\boldsymbol{y}}_i = \sqrt{n}\, \Sigma_0^{-1/2}(\overline{\boldsymbol{x}}_i - \boldsymbol{\mu}_0) \tag{7}$$

The out of control situation in the process tends to occur immediately upon$max_{\|a\|=1} C_i^a > h$. *h* is the upper control limit of control chart PPCUSUM. Moreover, to calculate the value of $\boldsymbol{C}_i^a$to be used for plotting points on a control chartcan be done using the following equation:

$$max_{\|a\|=1}C_i^a \geq \|\bar{y}_{i-j}+..+\bar{y}_i\| - (j+1)k \quad (8)$$

When the signal outside the control limit appears, the analysis at which state the process has become out of control can be made using:

$$\begin{cases} S_0 = 0 \\ S_i = \Sigma_{j=1}^{i}\bar{y}_j i = 1,2,\ldots. \end{cases};$$

$$C_i = \max\{0, \|S_i - S_{i-1}\| - k, \|S_i - S_{i-2}\| - 2k, \ldots, \|S_i - S_0\| - ik\} \quad (9)$$

At the time of the signal from the out of control processhappens in the time period $i_o{}^{th}$, then at the same time there will be a period of time i_1. The direction of the shifting process that has occurred can be determined using the following equation:

$$\hat{a}_0 = \frac{(s_{i_0} - s_{i_1})}{\|s_{i_0} - s_{i_1}\|} (10)$$

whereas the time at which the shift happens can be determined using this equation:

$$time\ shift\ occured = i_n + 1 (11)$$

In addition, the limits of the control chart can be determined using the formula projectedby Ngai and Zhang (2001), specifically in the cases where the value of k = 0,5 with C_0 and C_1 are constants with a specific value. The formula is like this:

$$\log(ARL) = c_0 + c_1 h (12)$$

$$c_o = \begin{cases} 0{,}6899, when\ p = 2, k = 0{,}5; \\ -0{,}0120, when\ p = 3, k = 0{,}5; \\ -0{,}1714, when\ p = 4, k = 0{,}5; \end{cases}$$

$$c_1 = \begin{cases} 0{,}8438, when\ p = 2, k = 0{,}5; \\ 0{,}8159, when\ p = 3, k = 0{,}5; \\ 0{,}7368, when\ p = 4, k = 0{,}5; \end{cases}$$

1.1 Research Data

The data used in this research are secondary data whichare sourced fromTukhfatul Mardiliyah (2009)taken from PT, Semen Gresik. The data reflects the condition of theordinary Portlandcement (OPC) from April to October 2008. There are four quality characteristics which are used as parameters and they areas follows:

1) *free lime*: Levels of free lime (%)
2) SO_3: Levels of sulfate (%)
3) CaO: Calcium oxide (%)
4) *Mesh*: Fineness cement is measured with a sieve (mμ)

The data were taken twice a day that is in the morning and in the afternoon. 4 subsamples were taken every time. To fulfil with the need of PPCUSUM control chart, two sets of data were taken. The firstset is the training data which were taken from April 5 until August 7, 2008 and the second set is the testing datawhich were taken from August 9 to October 18 2008.

OUTCOME

Table 1 shows the values acquired of the correlation between twoparameters. When *p*-value is greater than α = 0.05; it shows thatthere is no correlation between two variables. The only exception is the *p-value* of variable Free lime and SO3, which has less significance of α = 0.05 indicating that there is a correlation between the two variables. In addition, in this case the correlation between each variable is too small. The correlation from variable free lime and *CaO*, *CaO*and *Mesh* are inversely correlated, and this is obvious from the negative value of coefficient correlation between those variables.

Table 1. Value of Correlation Between Parameters OPC Cement

Parameters	Correlation (*p-value*)
Free lime and SO_3	0,141 (0,001)
Free lime and *CaO*	-0,004 (0,916)
Free lime and *Mesh*	0,023 (0,592)
$SO_3$and *CaO*	0,014 (0,742)
$SO_3$and*Mesh*	0,048 (0,254)
*CaO*and *Mesh*	-0,003 (0,951)

The test outcomes acquired and constructed using the chi-square quantile plots shapedstraight line (see Figure 1) and the value of *t*is 0.516447. It canbe seen that there is more than 51.65% of$d_i^2 \le \chi^2_{4;0.05}$. Consequently, it can be concluded that the training data have a multivariate normal distribution.

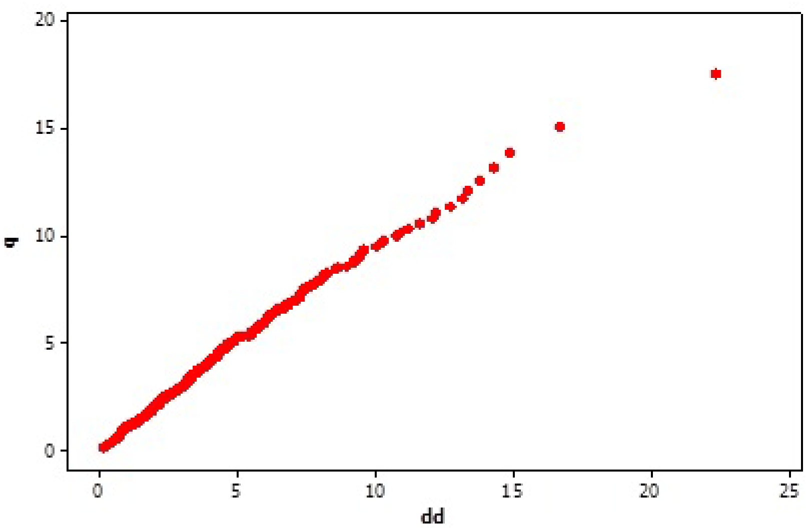

Fig. 1. Q-Q Figure Cement OPC Data

In PPCUSUM control chart, the control boundary and ARL must be precise before scheming the CUSUM value into a graph. Table 2 illustrates that there are five control limits and the control limit for PPCUSUM control chart with 4 parametersand the value of k = 0.5. With h

= 12.33, the Value of ARL is about 7427.16. As for the maximum control perimeter where *h* = 18.00, the value of ARL is about 485512.26.

Table 2. Control Perimeter (h) and ARL with p=4 and k =0,5

Batas Kendali (*h*)	ARL
12,3294	7427,165
13,0154	12312,087
13,7009	20403,341
14,3862	33805,05
18,0027	485512,26

Figure 2 illustrates the PPCUSUM control chart with 3 kinds of control limits (*h*). The control perimeter has been chosen randomly from Table 2. When *h* = 12.33 the first sample which is discovered to beoutside the control limit is sample10. When *h* =13.70 and *h* = 18.00 the first sample which is found to be outside the control limit is sample 16. The graph shows the pattern of the control chart in which the plotting point has a trend to amplify (Figure 2). In addition the pattern formed in the control chart shows that there is no firm patterns are formed. Detection of samples that are outside the control limits needs the interpretation of the shift when the process started and the direction of optimal shift process. A control chart is necessary to help in the explanation of the direction and starting time of a shifting process for a point that is outside the control limits.

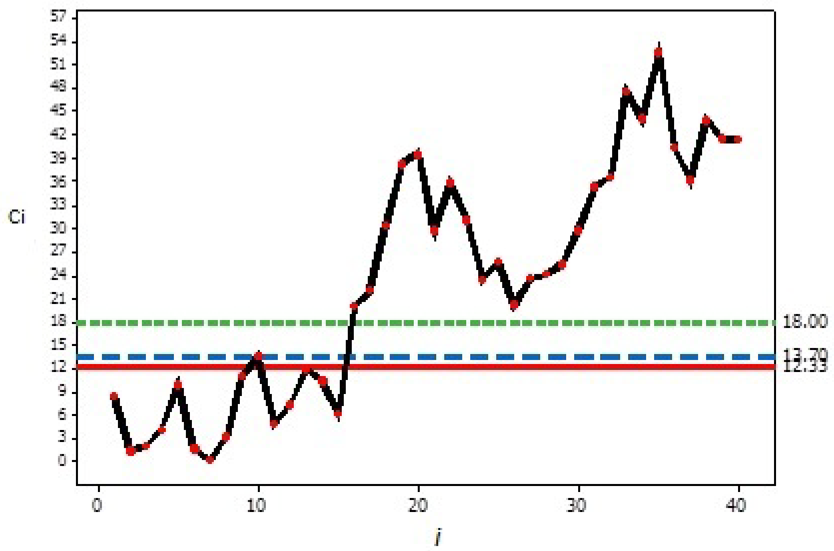

Fig. 2. PPCUSUMdiagram

Figure 3 has shown that the control chart more rapidly to amplify. Using the control limit h = 18.0026 (Figure 2), the first sample that is discovered to be outside of the control chart is sample number 16,while in Figure 3, the first sample found to be outside the control limit issample number 10. With equation (9), (10), (11) the value $\hat{\imath}_6$ = 6.694012 is obtained.Consequently, it is evident that the process began to shift towardsan uncontrolled condition at samples number8 with the average shift optimal process of$\hat{a}_0^T$ = (0.962416; 0.235219; 0.125824; 0.05094).

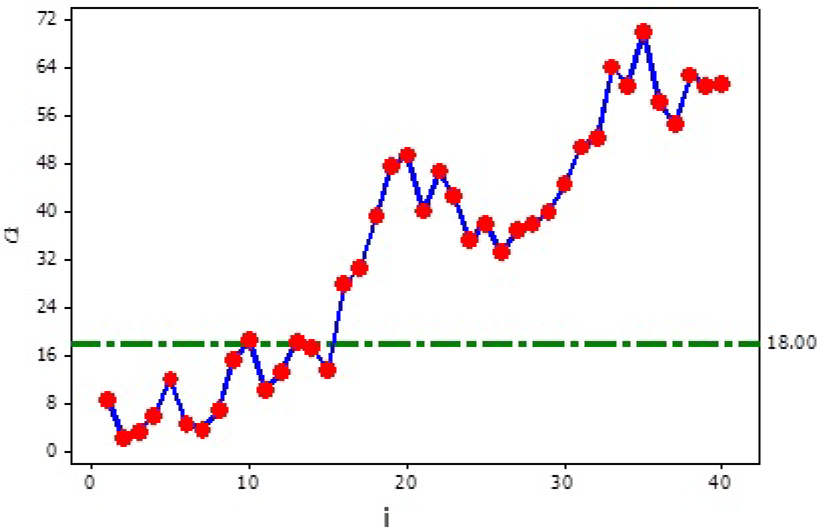

Fig. 3. UncontrollablePPCUSUM Chart

DEBATE

The correlation has a series value of 0-1; if the correlation value is nearer to 1, then the relation between the two parametersis greater. Based on the results in Table 1, it is obvious that the correlation between each variable is very small. In the same table, it can be seen that there are 2 negative values of correlation. The negative value occurs due toX_1having a big value and is associated with the small correlation ofX_2. Consequently, it can be said that parametersX_1 and X_2 has a negative correlation [17]. The use of PPCUSUM control chart can be applied to the data that correlate partially or simultaneously. If it isan independent variable, then each variable can be described in univariate charts. If multivariate control charts are used on*p*-variables that are not correlated, then the results of the multivariate and univariate control charts will be the same [18]. In this paper, four parametersare observed simultaneously due to the fact that the four variables are mixed together without compromising the other materials. Separate observation of the product with many quality characteristics would take a longer timeto be analyzed and may lead to the wrong explanation of the quality control results [19-25]].

Determination of the control limits *h* and the ARL will affect each other. The larger value of the targeted ARL will directly result in an increasingly wide control limit. It can be concluded that a small value of *h* will result in a small value of ARL too. This will result in a control chart that is more sensitive to the shifting process. Dissimilarly, greater values of h will result in a greater value for ARL [26-30]. It takes 5 types of control limits (*h*) to construct the PPCUSUM control chart in this study. Each type of the control limit (*h*) has its own value of ARL. For the lowest value of *h*, which is 12.33, the ARL value is about 7427 meanwhile for the highest value of *h*, which is18.00, the ARL value is about 485512. ARL means the number of products that have been produced before the first product become out of control. For example with *h* = 12.33, it indicates that there are 7427 products have been produced before the first out of control signal appears [31-35].

The out of control signal from the process in the CUSUM chart does not indicate a bad production. Rather, it raises the need for the production process to be checked with necessary actions to follow later. In Figure 2, the PPCUSUM control chart shows that 40 samples have been checked to monitor the quality of the product. It was discovered that there are only 14 samples which are under the control limit with *h* = 12.33. It was also found that the first sample detected to be outside the control limit is sample number 10. Samples number 11 to samples number 15 were back under the control limit. However, after sample number 15, the production process went completely out of control. With *h* = 18, there are 15 samples which are under control and the first sample discovered to be outside the control limit is sample number 16.Samples number 17 to 40 is out of control. CUSUM uses a method which accumulates the vector *X,* and then makes a quadratic form from that. In this method, the PPCUSUM control chart will depend on the magnitude between each sample [36-40].

Figure 2 shown there is a rise in the number of shifting that happens in the production process. It is due to the fact that the magnitude from each sample is too big especially in the variable free lime. Apart from considering the trend, the control chart also considers the special pattern on the graph. Other studies have shown that there are differences in the pattern of the MCUSUM type control chart with other control charts. Other control charts such as theT^2Hostelling and MEWMA have a more random pattern as compared to MCUSUM type control chart; as suggested by Waterhouse *et. al.*, (2010) and Talib *et. al., (*2014). According to Waterhouse *et. al* [14], they applied the T^2 Hotelling, MEWMA and MCUSUM clinical setting. From the chart, it was shown that the MCUSUM control chart have more patterns than other charts [41-43].

The capability of control chart can also been seen from the time taken by the control chart in detecting shifts in production process. MCUSUM control chart approach to Projection Pursuit is a method which detects the shift faster than other control charts. However, the effectiveness of PPCUSUM as compared to MC1 or MEWMA has been shown by Ngai and Zhang (2001). The PPCUSUM chart has given an out of control signal at the 4th sample while the MC1 and MEWMA failed to detect the shift. In this study with using *h* = 18,00 the first sample outside the control limit is sample number 16 but with the Projection Pursuit approximation it can be known the process started to shift into out of control since the sample number 8 [44-46].

CONCLUSION

Based on the results and discussions, it can be concluded that PPCUSUM control chart is an effective method to analyse small shifts in production process. It is also a quick detector of the signs indicating that a process is starting to shift into out of control condition. The data generated from the application of PPCUSUM control chart on the production of OPC cement indicated that there were a significant number of points outside the control limit. Due to the sensitivity of the control chart, the number of observation points indicates the out off control situations in this case due to the magnitude of the deviation or distance between valuesof each sample, without ruling out the possibility of errors in the production process. Therefore, PPCUSUM control chart is more effective in monitoring a production process with high precision system such as in chemistry or in textile industry.

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