ENHANCED KNOWLEDGE IN SCIENCES AND TECHNOLOGY
e-ISSN: 2773-6385

EKST

Vol. 4 No. 2 (2024) 181-190
https://publisher.uthm.edu.my/periodicals/index.php/ekst

Root Cause Analysis on Process Monitoring in Ammonium Sulphate Fertilizer Production

Lam Heng Loong[1], Rohayu Mohd Salleh[1]*

[1] *Department of Mathematics and Statistics, Faculty of Applied Sciences and Technology, UTHM Kampus Cawangan Pagoh, Hab Pendidikan Tinggi Pagoh, KM 1, Jalan Panchor, 84600 Pagoh, Muar, Johor, MALAYSIA*

*Corresponding Author: msrohayu@uthm.edu.my
DOI: https://doi.org/10.30880/ekst.2024.04.02.022

Article Info

Received: 27 December 2023
Accepted: 11 January 2024
Available online: 12 December 2024

Keywords

ZA Fertilizer, Root Cause Analysis, IGV Chart, VV Chart, TCV, Multivariate, Subgroups

Abstract

Ammonium sulphate, often known as ZA fertilizer, was extensively employed nitrogen (N) fertilizers for crop cultivation in Malaysia. While ZA fertilizer has been widely used for increased crop yields, concerns about its inconsistent performance despite application have risen. Hence, this study delves into the root causes of this issue. There are two phases in process monitoring which are Phase I implemented 30 subgroups while Phase II implemented 14 subgroups with 5 critical-to-quality, CO_2, NH_3, ratio of CO_2/NH_3, specific weight and temperature respectively. Before revealing the root cause, IGV and VV control charts were implemented to monitor the process variability in the production. Process monitoring analysis using IGV and VV charts revealed the VV chart's superior sensitivity in detecting variations, particularly for the eight samples exhibiting out-of-control signals which are 2nd sample, 5th sample, 6th sample, 10th sample, 11th samples, 12th sample, 13th sample and 14th sample respectively. By comparing performance of the both chart in detection of out-of-control signals, VV chart have better performance compared to IGV chart. Further investigation of Root Cause Analysis using TCV on the eight out-of-control signals, it was identified CO_2 followed by NH_3 as key contributors to these inconsistencies. Hence, CO_2 and NH_3 need to be focused and solid plans should be developed to address each root cause.

1. Introduction

In 2021, Malaysia imported RM4.3 billion worth of fertilizers from China, USA, Indonesia, Canada, and Russia, which gives a significant financial outlay [1]. This financial commitment demonstrates how vitally dependent the country is on outside funding to maintain its level of agricultural productivity. Ammonium sulphate's (ZA)extensive use in Malaysian agriculture is evidence of its dominance in the nation's nitrogen fertilizer market [2].

Despite its widespread use in Malaysian agriculture, ZA fertilizer's inconsistent quality and effectiveness stem from fluctuating ammonia and carbon dioxide levels, crucial for optimal crop growth. This issue has the potential to result in scarcity of food and harm the ecosystem. In order to optimize crop yields, Malaysian farmers must meticulously maintain a harmonious equilibrium of nutrients in their soil. The fertilizer business is currently prioritizing the assurance of the quality of ZA fertilizer. An approach to accomplish this is to closely observe the production process to ensure that there is an appropriate quantity of each ingredient, avoiding both excessive and insufficient amounts. This can be done using statistical process control methods, such as control charts [3]. Implementation of the control chart is essential as it can show clearly whether a process is running within or outside of its expected range of variation.

However, in monitoring several quality characteristics at the same time, a univariate control chart may not hold up in the complex pattern created by intercorrelated quality parameters in the multivariate processes. Therefore, a more advanced technique is needed. The challenge of concurrently monitoring variables that are associated has been addressed by several multivariate control chart approaches, including the Hotelling T^2 chart and Multivariate Exponentially Weighted Moving Average chart (MEWMA). In an area of interest involving a multivariate process, process mean is typically monitored using the Hotelling T^2 chart, while process variability is typically monitored using the Generalized Variance chart [4].

It becomes critical to interpret the out-of-control signals as abnormality in the process occurred. Although detecting out-of-control is crucial, the study underscores that it forms the initial stage of a thorough investigation. Therefore, Root Cause Analysis (RCA) becomes crucial for identifying and tackling underlying issues [5]. Often, manufacturers overlook variations in ZA fertilizer components and instead cite machinery or equipment issues as the source of out-of-control signals. This erroneous assumption necessitates root cause analysis (RCA) to uncover the underlying reasons for the problem. RCA can effectively pinpoint and address the root causes, leading to advancements in ZA fertilizer production.

This research aims to study the root cause analysis of the process monitoring and three objectives were set up. The first objective is to monitor the process variation in the multivariate data by using the IGV and VV charts. Followed by the second objective, aims to compare the performance of the IGV chart and VV chart in the detection of out-of-control signals. The last objective is to analyse the root causes of out-of-control signals using TCV. These objectives collectively yield valuable insights into improving quality control processes in the ZA fertilizer production industry.

2. Materials and Methods

This section will discuss the methodology included in the study. Dataset Descriptions, Preliminary analysis, IGV chart, VV chart and TCV are clearly explained in detail.

2.1 Data Description

This study applies ZA fertilizer Dataset to monitor the process variability and this data sets are available at https://www.tandfonline.com/doi/pdf/10.1080/23311916.2019.1665949 [6]. The data taken from the production process of ZA fertilizer at Carbonation level in Gresik [6]. The dataset consists of 44 observations with 12 subgroups. ZA fertilizer has five quality characteristics as shown in Table 1. The ZA fertilizer data were collected from July to the end of August in the year 2003. This study included two stages; 30 subgroups were employed in Phase I and 14 subgroups in Phase II. ZA fertilizer is vital as it increases the yield of the crop in agriculture sectors. If the quality of the ZA fertilizer is not maintained consistently, it will create negative effects to the crops and environments such as increased pH value in the soil.

Table 1 Data Description

No.	CTQ	Units	Subgroups	Subgroup size
1	CO_2	g/L	44	12
2	NH_3	g/L	44	12
3	Ratio CO_2 / NH_3	-	44	12
4	Weight	kg/L	44	12
5	Temperature	^0C	44	12

2.2 Preliminary Analysis

There are 3 assumptions that need to be conducted before constructing the IGV and VV chart. Since this study uses multivariate data, the multivariate normality assumption, independence of observations, and dependency between variables must be met.

2.2.1 Multivariate Normality Testing

Previous research considered multivariate data were assumed to follow the multivariate normal distribution [7]. Many multivariate normality tests exist, including Henze-Zirkles, Mardia's, and Anderson Darling. Utilizing the graphical approach such as QQ plot with test statistics to test multivariate normality improves data normality judgement [8]. The normality plot, also known as the Q-Q plot, is plotted for the multivariate normality assumption by calculating the T^2 values versus the beta quantile in order to identify any patterns of linearity in the data.

Enhanced Knowledge in Sciences and Technology Vol. 4 No. 2 (2024) p. 181-190

2.2.2 Correlation Checking

The utilization of the correlation coefficient has been frequently employed to assess the association between two distinct variables [9]. The correlation coefficient needs to be conducted before data analysis to clarify the relationship of the variables [10]. The general form of the Pearson correlation coefficient is shown in equation (1),

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{\left[n\sum x^2 - (\sum x)^2\right] * \left[n\sum y^2 - (y)^2\right]}} \tag{1}$$

where x is the respective observation for the first variable, y is the respective observation for the second variable and n is the sample size.

P-value hypothesis testing will be used to determine whether the outcome is statistical. The hypothesis testing will be shown as below:

$$\begin{aligned} H_0 &: p_{xy} = 0 \text{ (two variables uncorrelated)} \\ H_0 &: p_{xy} \neq 0 \text{ (two variables correlated)} \end{aligned} \tag{2}$$

When the p-value is smaller than the alpha value, it indicates that the H_0 is rejected and concluded that there exists a linear association between the two variables and vice versa.

2.2.3 Lag Test

One of the assumptions that needs to be made is the independency of observations [11]. The lag test determines if the observation and lag-1 are associated. Each observation is paired with the next until n-1 is made.

Hypothesis testing with the p-value will determine the correlation coefficient between observation and lag-1 observation to improve scatter plot assessment [12]. The hypothesis testing is shown in equation (3):

$$\begin{aligned} H_0 &: p_{X1,\, lag-X1} = 0 \\ H_1 &: p_{X1,\, lag-X1} \neq 0 \end{aligned} \tag{3}$$

When the p-value is less than the alpha value, H_0 is rejected and a linear relationship between observation and lag-1 is concluded and vice versa.

2.3 Multivariate Process Monitoring Chart

When monitoring process variability with correlated variables, the multivariate control chart is preferred and more suitable than the univariate chart. This study monitored process variability with IGV and VV control charts. IGV and VV charts are Shewhart-type charts that can detect sudden process variability changes [13]. Then, both charts were compared for out-of-control point detection.

2.3.1 IGV Control Chart

The sample variance-covariance matrix determinant measures variability numerically. The determinant of the sample variance-covariance matrix is called generalized variance (GV), abbreviated as |Σ| for population and |S| for sample. Djauhari introduced the standard GV chart to improved GV chart (IGV) to eliminate bias [14]. The formula to construct the IGV chart is shown as equation (4) until equation (6).

$$LCL = \max\left(0, \left|\overline{S}\right|\left(\frac{b_1}{b_3} - 3\sqrt{\frac{b_1}{{b_3}^2 + b_4}}\right)\right) \tag{4}$$

$$CL = \left|\overline{S}\right|\frac{b_1}{b_3} \tag{5}$$

$$UCL = \left|\overline{S}\right|\left(\frac{b_1}{b_3} + 3\sqrt{\frac{b_1}{{b_3}^2 + b_4}}\right) \tag{6}$$

where $\left|\overline{S}\right|$ denoted as the determinant of sample average of the covariance matrix, b_1, b_2, b_3 and b_4 are constants.

2.3.2 VV Control Chart

[15] introduced the VV chart to monitor process variability simultaneously with the IGV chart. To construct the VV chart, the formula to compute LCL, CL, and UCL was shown in equation (7), equation (8) and equation (9).

$$LCL = \max\left(0, \theta - 3\eta\right) \tag{7}$$

$$CL = \theta \tag{8}$$

$$UCL = \theta + 3\eta \tag{9}$$

where θ denotes the sigma and η represents the standard deviation of the covariance matrix.

2.3.3 Total Conditional Variance

TCV was implemented as a tool to find the root cause of the out-of-control signals. TCV was presented by Djauhari in 2016 and was based on statistical diagonalization developed by Mustonen in 1997 [16], [17]. The TCV chart can show which variables most affect variance variation by the ordering of variables based on their respective sample covariance matrices, enabling a straightforward identification of the primary reason [18], [19]. Unlike IGV and VV, the TCV used Cholesky decomposition assumptions to compute the covariance matrix. The formula to construct TCV was computed as shown in equation (10) until equation (13).

$$S_k = \frac{1}{n-1}\sum_{k=1}^{m}\left(X_k - \overline{X}\right)\left(X_k - \overline{X}\right)^t \tag{10}$$

$$TCV_k = \sum_{k=1}^{p} s_{ii.123\ldots(i-k):k} \tag{11}$$

$$TCV_{\bar{s}} = \sum_{i=1}^{p} s_{ii.123\ldots(i-k):\bar{S}} \tag{12}$$

$$UCL = \mu + 3\sigma \tag{13}$$

In equation (10), the assumption by Cholesky decomposition, covariance matrix S_k will be calculated for all k = 1, 2, …, m. Then, in equation (11) and equation (12), the TCV value for each group and the estimated TCV value based on the average covariance matrix of all subgroups are computed respectively. Lastly, the general form of UCL for TCV is showed in equation (13) where μ denotes the sigma and σ represents the standard deviation of the covariance matrix.

3. Results and Discussions

3.1 Preliminary Analysis

The computation of the correlation coefficient between X_2, X_3, X_4 and X_5 with X_1 was performed. The correlation coefficients for the X_2, X_3, X_4 and X_5 with X_1 are illustrated in Table 2. *P*-value that less than alpha value of 0.05 indicates that the variables are correlated.

According to Table 2, variables X_1 and X_3 exhibit a moderate positive correlation, while variables X_1 *and* X_2, X_1 and X_4, and X_1 and X_5 exhibit weak positive correlations. Besides that, *p*-value for all variables is less than 0.05. Hence, it can be concluded all pairwise correlations are statistically significant.

Table 2 Correlation Matrix for X1, X2, X3, X4, and X5

Variable	Coefficient of correlation	Results	*p*-value
X_2	0.340	Weak positive correlation	0.000
X_3	0.616	Moderate positive correlation	0.000
X_4	0.315	Weak positive correlation	0.000
X_5	0.433	Weak positive correlation	0.000

From Table 3, the *p*-values for X_1, X_5 and their respective lag-1 values were statistically significant (p<0.05), indicating correlation. The null hypothesis was rejected for these pairs. For X_2, X_3, and X_4, the *p*-values (0.300, 0.184, and 0.885) exceeded the alpha level (0.05), leading to acceptance of the null hypothesis, indicating no correlation. Since not all pairs were uncorrelated, the assumption of independence was violated. However, this study focuses on control charts for multivariate normal processes, assuming independent observations [20].

Enhanced Knowledge in Sciences and Technology Vol. 4 No. 2 (2024) p. 181-190

Table 3 Correlation coefficient and p-value between variables and their lag-1

Variables	Correlation	*p*-value
X_1 vs lag-X_1	0.654	0.000
X_2 vs lag-X_2	0.199	0.300
X_3 vs lag-X_3	0.254	0.184
X_4 vs lag-X_4	0.028	0.885
X_5 vs lag-X_5	0.690	0.000

The first 30 samples were calculated to determine the T^2 values for each individual observation. Fig. 1 depicted the multivariate normality plot, specifically the QQ plot for T^2 vs beta quantiles.

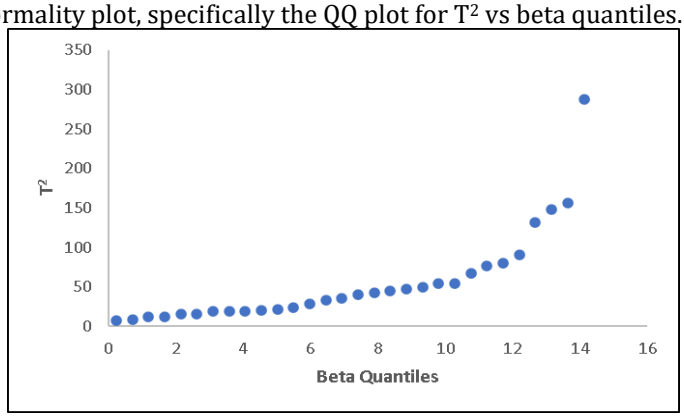


Fig. 1 QQ plot for T^2 versus Beta Quantiles

Fig. 1 shows that the ZA fertilizer data does not follow a multivariate normal distribution due to an outlier. This outlier may indicate an out-of-control situation in the production process. When a QQ plot indicates the presence of outliers in the context of process monitoring, it implies that there are deviations from the anticipated distribution of data points. Hence, statistical process control using IGV and VV charts will be implemented to investigate the possibility of out-of-control situation in the production process.

3.2 IGV Chart Phase I Monitoring

In Phase I of monitoring process variability involved the analysis of data from 30 subgroups, each consisting of 12 observations, and encompassing a total of 5 variables.

To compute the average of the sample covariance matrix, denoted as $\bar{S}$, the covariance matrix for the m=30 subgroups was computed in Phase I. The $\bar{S}$ were calculated and the results are shown in equation (14).

$$\bar{S} = \begin{pmatrix} 167.0636 & 32.4151 & 0.5430 & 0.6745\times10^{-1} & 4.0780 \\ 35.7207 & 110.1500 & -0.3109 & -0.2134\times10^{-1} & -1.0656 \\ 0.5430 & -0.3101 & 0.4283\times10^{-2} & 4.082\times10^{-4} & 0.2215\times10^{-1} \\ 0.0674 & -0.0213 & 0.4082\times10^{-3} & 6.020\times10^{-4} & 0.2207\times10^{-2} \\ 4.0780 & -1.0656 & 0.2215\times10^{-1} & 0.2207\times10^{-2} & 2.0765 \end{pmatrix} \quad (14)$$

The determinant of average of covariance matrix $|\bar{S}|$ = 0.01492, b_1 = 0.3442, b_2 = 0.2116, b_3 = 0.9700 and b_4= 0.02903. The corresponding determinant of covariance matrix, $|S_k|$ for each sample were computed. $|S_k|$ for each sample and summarized in Table 4.

Table 4 Value of $|S_k|$ for each sample

Sample, k	$\lvert S_k \rvert$	Sample, k	$\lvert S_k \rvert$	Sample, k	$\lvert S_k \rvert$
1	2.81E-08	11	1.16E-07	21	1.05E-07

2	0.004008	12	1.67E-07	22	3.86E-05
3	2.1E-08	13	1.01E-06	23	4.93E-08
4	3.1E-07	14	6.04E-06	24	1.74E-09
5	0.000193	15	7.83E-06	25	4.56E-09
6	5.6E-08	16	0.0003	26	1.48E-05
7	1.25E-07	17	1.42E-06	27	0.015069
8	4.04E-05	18	4.96E-07	28	4.89E-06
9	8.49E-07	19	3.93E-07	29	8.79E-05
10	2E-06	20	2.17E-06	30	1.41E-07

Based on the above calculations, the trial upper control limit (UCL) and lower control limit (LCL) were determined. The LCL was found to be -0.01561, which has been set to 0, while the UCL was calculated to be 0.020906. Subsequently, the IGV was assembled and visually depicted in Fig. 2.

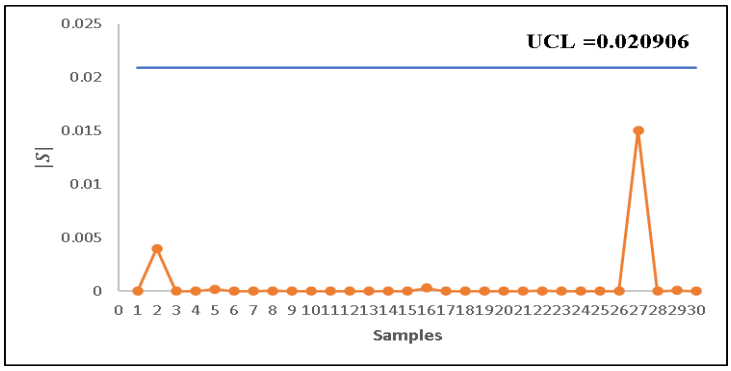


Fig. 2 IGV chart for Phase I

Fig. 2 reveals that all of the samples exhibit a state of control. No samples in the dataset surpass the higher control limit or fall below the lower control limit. Consequently, the control limits utilized for Phase II monitoring will be derived from the trial control limits.

3.3 VV Chart Phase I Monitoring

The determination of the value of VV for each sample k was executed by summing all the diagonal elements of S_k^2. The values of $Tr(S_k^2)$ for each sample are presented in Table 5.

Table 5 Vector Variance for each sample

Sample, k	$Tr(S_k^2)$	Sample, k	$Tr(S_k^2)$	Sample, k	$Tr(S_k^2)$
1	8872.617	11	4910.888	21	17541.78
2	193986.570	12	64028.64	22	35568.64
3	7138.315	13	26149.42	23	13092.11
4	3053.349	14	1624.618	24	7305.709
5	137842.5	15	208392.4	25	3451.94
6	14116.57	16	289719.4	26	1191583
7	26911.99	17	6693.221	27	170172.6
8	565170.9	18	18180.17	28	109678.8
9	65998.36	19	12494.87	29	41419.11
10	24276.33	20	9856.567	30	4049.554

In order to perform the control limit calculations, it is necessary to consecutively compute the matrix S, its square $\overline{S}^2$, the sum of all diagonal components of $\overline{S}^2$, and the sum of squares of all elements of $\overline{S}^2$. This process

Enhanced Knowledge in Sciences and Technology Vol. 4 No. 2 (2024) p. 181-190

yields a value of 42399.6844 for the $Tr(\bar{S}^2)$ and a value of 1201281729 for $Tr(\bar{S}^4)$. Hence, the estimated values for θ and η are 50410.1182 and 30323.9797 respectively. Consequently, the LCL is determined to be -1.17623, which is adjusted to 0, and the UCL = 1.81712. The VV chart for the Phase I first trial was depicted in Fig. 3.

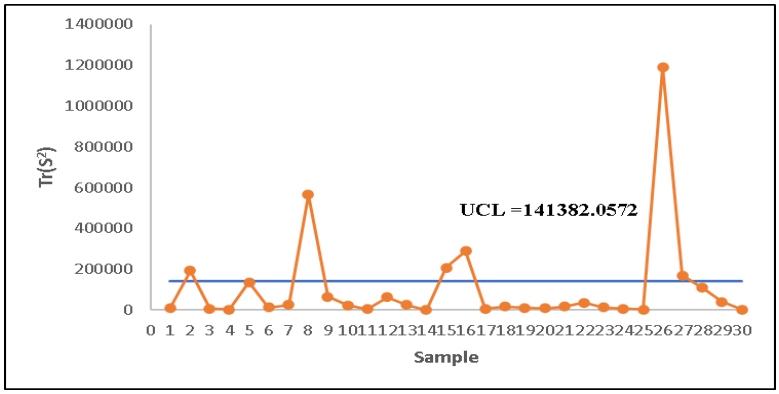
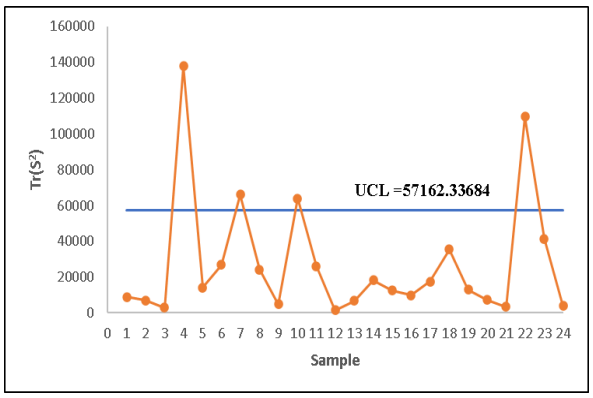


Fig. 3 VV chart for Phase I

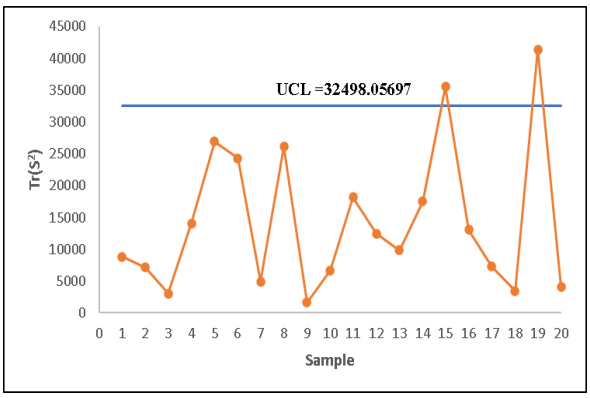
As demonstrated in Fig. 3, there are six samples that exceed the upper control limit, indicating an out-of-control process. The samples are discarded and the control limit revised until the process stabilizes. Results and VV charts for subsequent iterations are shown in Table 6 and Fig. 4 respectively.

Table 6 Results of each iteration for VV chart

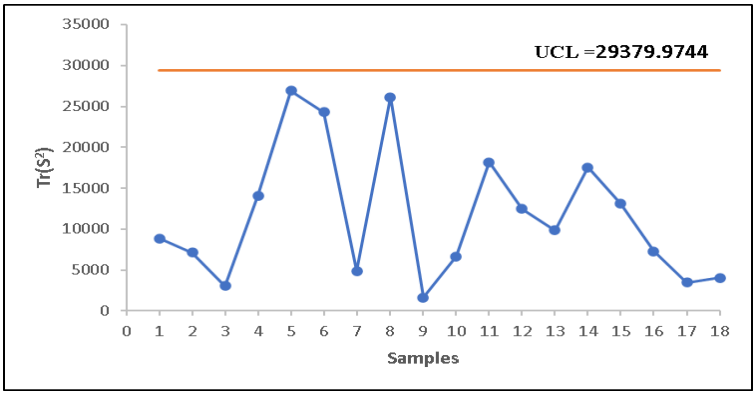
Trial	$Tr(\bar{S}^2)$	$Tr(\bar{S}^4)$	UCL	LCL	No. of samples remove
2nd	16660.7253	204001175.2	57162.33684	0	4
3rd	9874.5628	63437145.23	32498.05697	0	2
4th	8736.665008	53363166.73	29379.97441	0	0



(a)



(b)



(c)

Fig. 4 VV chart for phase I monitoring (a)second trial (b) third trial (c) fourth trial

In the fourth trial, $Tr(S^2)$ and $Tr(S^4)$ were 8736.67 and 53363166.73, respectively. For θ and η, the values were 10428.40 and 6317.19, respectively. Based on these estimates, the UCL to be 29379.97, but the lower control limit (LCL) was negative. Therefore, LCL was adjusted to 0. The VV chart for this trial shows that all the samples are within the control limits as shown in Fig. 4 (c), meaning the process is in control. Therefore, the control limits from this trial will be implemented for the next phase of monitoring.

3.4 Phase II Monitoring

In Phase II process variability monitoring, m = 14 samples will be monitored in this phase, with each sample having a size of n = 12 and variables p = 5.

The control limits for the IGV and VV chart derived during Phase I will be applied during Phase II operations. The $|\bar{S}|$ for the 14 observations will be displayed in Table 7. Subsequently, Phase II IGV chart will be shown in Fig. 5 while Phase II VV chart will be displayed in Fig. 6.

Table 7 $|\bar{S}|$ value and Vector Variance for each sample.

Sample, k	$\lvert S_k \rvert$	$Tr(S_k^2)$	Sample, k	$\lvert S_k \rvert$	$Tr(S_k^2)$
1	3.630E-08	12433.8904	8	5.541E-08	14127.0213
2	1.578E-06	34972.4987	9	7.166E-08	29014.2259
3	3.064E-06	17108.4132	10	1.010E-06	253337.1612
4	9.795E-09	12907.4846	11	2.421E-05	44233.5509
5	0.003772	157671.3389	12	5.650E-07	32831.9719
6	0.009000	582883.4317	13	3.340E-06	111475.7327
7	3.698E-07	10596.4971	14	9.749E-06	32297.4112

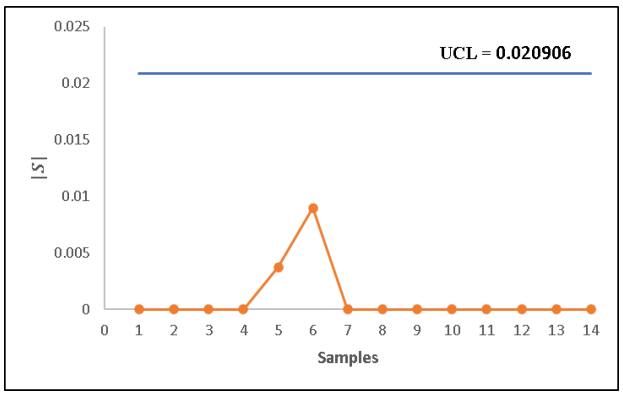


Fig. 5 IGV chart for Phase II Monitoring.

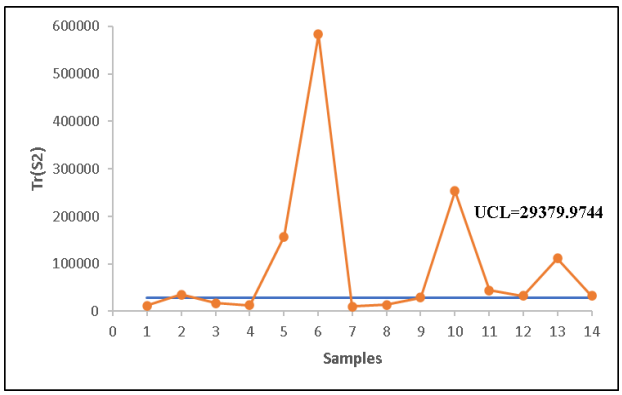


Fig. 6 VV chart for Phase II Monitoring.

In Fig. 5, it is demonstrated that every sample falls inside the control limits area. Thus, it indicates that the process is in a state of control for IGV chart. From Fig. 6, it's evident that eight samples surpass the UCL. This indicates that the process is not in control.

By comparing both charts, the VV chart seems to be outperformed than the IGV chart in detecting out-of-control signals. In other words, VV charts have high efficiency in detecting changes in process variability.

3.5 Total Conditional Variance (TCV)

The most significant factors influencing variability are identified by examining the sequence of X variables. The rank order of variables corresponding to the trace value is shown in Table 8.

Table 8 Rank order of variables and corresponding trace value

Observations	Trace value	Order of variables
2nd Observation	194.052	X_1,X_2,X_5,X_3,X_4
5th Observation	401.023	X_1,X_2,X_5,X_4,X_3
6th Observation	862.427	X_1,X_2,X_5,X_3,X_4
10th Observation	510.920	X_1,X_2,X_5,X_3,X_4
11st Observation	257.593	X_1,X_2,X_5,X_3,X_4
12nd Observation	240.929	X_1,X_2,X_5,X_3,X_4
13rd Observation	341.348	X_1,X_2,X_5,X_3,X_4
14th Observation	186.431	X_1,X_2,X_5,X_3,X_4

The eight out-of-control points from VV charts analyzed by using TCV to identify the root cause. It is important to determine the root cause that contributes to the process variability within the five variables. The variables are sorted based on the maximum trace value.

Concerning Table 8, the order of variables for all out-of-control points are mostly the same. Variability for all of the out-of-control points is majorly contributed by X_1 (CO_2), followed by X_2 (NH_3). The least contributed variable for 5th observation is different with others observation, which is X_3 (ratio of CO_2/NH_3) is the least contributed variable for 5th observation while other observations are X_4 (specific weight) variable.

In Failure Mode and Effect Analysis context, inaccurate measurement of raw materials could pose a significant risk of product defects and should be considered a critical failure mode. This can result in the production of fertilizers with the wrong nutrient ratios, which can have a detrimental effect on plant development and yield. The production process can be changed to include routine calibration of measuring equipment and raw material quality inspection in order to prevent erroneous measurement of raw materials. Fertilizer production costs can be decreased and product quality can be enhanced by employing RCA to detect the root cause.

4. Conclusion

All of the objectives; monitor the process variability by using IGV and VV charts, compare the performance of both charts and analyze root cause by using TCV were achieved. It was determined that in monitoring the variability in ZA fertilizers, VV chart has a better performance than IGV chart in detecting out-of-control signals. This result findings enable the manufacturer to implement higher performance chart to monitor the process variability in ZA fertilizer for enhancing the quality of ZA fertilizer. Besides that, the eight out-of-control signals were taken to the root cause analysis to identify the root cause. Results from the root cause analysis using TCV showed that carbon dioxide is the most contributing factor to the variability, followed by the ammonia. The manufacturer should examine and investigate the factors of carbon dioxide and ammonia to minimize product variability during the manufacturing process.

For future studies, researchers may investigate the effectiveness of TCV as compared to current root cause analysis techniques in most industries. This thorough analysis provides a valuable opportunity to not only confirm the suggested approach but also determine its superiority in identifying the underlying reasons among existing process variances. Through careful examination of practical situations and obstacles specific to various industries, these studies might provide useful insights that could facilitate the wider acceptance of TCV as a more precise and dependable approach for root cause analysis.

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Lam Heng Loong, Rohayu Mohd Salleh;* ***data collection:*** *Lam Heng Loong;* ***analysis and interpretation of results:*** *Lam Heng Loong, Rohayu Mohd Salleh;* ***draft manuscript preparation:*** *Lam Heng Loong, Rohayu Mohd Salleh. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] DOSM, 2022. *How Fertiliser Price Affected by the Global Situation*. Retrieved 10 October 2023 from https://v1.dosm.gov.my/v1/index.php?r=column/cone&menu_id=Q2NlamM5QUp2eTFyekEremxPcE9oZz09

[2] Academic of Science Malaysia (2023). *Ensuring Food Security: Ammonium Sulphate Fertilisers*. Retrieved 10 October 2023 from https://www.akademisains.gov.my/asm-focus/ensuring-food-security-ammonium-sulphate-fertilisers

[3] Xie, M. & Goh, T.N. (1999). Statistical Techniques for Quality. *The TQM Magazine, 11(4),* pp. 238-241.

[4] Yeh, A. B., Lin, D. K., Zhou, H., & Venkataramani, C. (2003). A Multivariate Exponentially Weighted Moving Average Control Chart for Monitoring Process Variability. *Journal of Applied Statistics*, *30(5)*, pp. 507–536.

[5] Wahed, M. A., Montaser, M. G., & Sami, S. A. (2010). Root Cause Analysis for Medical Equipment Calibration Laboratory Nonconformities. *Cairo International Biomedical Engineering Conference*, pp.206-209.

[6] Mashuri, M., Haryono, H., Aksioma, D. F., Wibawati, W., Ahsan, M., & Khusna, H. (2019). Tr(R2) Control Charts Based on Kernel Density Estimation for Monitoring Multivariate Variability Process. *Cogent Engineering*, 6(1).

[7] Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E. & Tatham, R. L. (2006). Multivariate Dara Analysis. 6th edition. New Jersey: Pearson Prentice Hall.

[8] Khatun, N. (2021). Applications of Normality Test in Statistical Analysis. *Open Journal of Statistics*, 11, pp. 113-122.

[9] Taylor, R. L. (1990). Interpretation of the Correlation Coefficient: A Basic Review. *Journal of Diagnostic Medical Sonography, 6(1)*, pp. 35-39.

[10] Obilor, E. I. & Amadi. E. C. (2018). Test for Significance of Pearson's Correlation Coefficient (r). *International Journal of Innovative Mathematics, Statistics & Energy Policies, 6(1),* pp. 11-23.

[11] Djauhari, M. A., Lee, L. S., & Salleh, R. M. (2016). Modeling Positive Time Series Data: A Neglected Aspect in Time Series Courses. *American Journal of Applied Sciences, 13(7),* pp. 860-869.

[12] Montgomery, D. C. (2009). Introduction to Statistical Quality Control. 6th edition. New York: John Wiley & Sons.

[13] Djauhari, M. & Mohamad, I. (2010). How to Control Process Variability More Effectively: The Case of a B-Complex Vitamin Production Process. *South African Journal of Industrial Engineering*, *21*, pp. 207-215

[14] Djauhari, M. A. (2005). Improved Monitoring of Multivariate Process Variability. *Journal of Quality Technology, 37(1)*, pp. 32-39.

[15] Djauhari, M. A., Mashuri, M., and Herwindiati, D. E (2008). A Multivariate Process Variability Monitoring. *Communications in Statistics–Theory and Methods, 37*, pp. 1742-1754.

[16] Djauhari, M. A. *Advanced Monitoring Techniques for Complex Process Variability in Manufacturing Industry*. 1st Ed. Universiti Putra Malaysia Press. 2016

[17] Mustonen, S. (1997). A Measure for Total Variability in Multivariate Normal Distribution. *Computational Statistics & Data Analysis, 23(3),* pp. 321-334

[18] Djauhari, M. A., Sagadavan, R., & Lee, L. S. (2016). Monitoring Multivariate Process Variability When Sub-Group Size is Small. *Quality Engineering, 28(4),* pp. 429-440.

[19] Djauhari, M. A., Sagadavan, R., & Lee, S. L. (2017). Monitoring the Disparity of Teaching and Learning Process Variability: A Statistical Approach. *International Journal of Productivity and Quality Management, 21(4),* pp. 532.

[20] Yeh, A. B., Lin, D. K., & McGrath, R. (2006). Multivariate Control Charts for Monitoring Covariance Matrix: A review. *Quality Technology and Quantitative Management, 3(4)*, pp. 415-436.