Monitoring Variability Process Of Water Quality PDAM Tirta Je'ne'berang Using MEWMV Control Chart

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Abstract

The demand for clean water is growing faster than the ability to supply it, so the proportion of the population that can be served by PDAMs is shrinking. PDAM Tirta Je'ne'berang is authorized to provide society drinking water services that meet the requirements. The laboratory at PDAM Tirta Je'ne'berang is used to measure and examine the quality characteristics used as a determinant of water quality, which include turbidity and the amount of dissolved solids. Water quality tests were performed in a multivariate manner, with the parameters used being normally distributed and correlated with one another. As a result, the MEWMV control chart, which can monitor variability, is used in this study. The water quality characteristics used are turbidity and chlorine, which are determined using the MEWMV control chart, weights ω, λ, and L. According to the findings of the analysis, the most sensitive weights in monitoring water quality variability were $\omega = 0.8$, $\lambda = 0.9$, and $L = 4.8004$, where no data is out of control in either phase, and thus the data has been statistically controlled. The weights $\omega = 0.8$, $\lambda = 0.9$ were chosen as the most optimal because they have the smallest difference from the value of Tr(Vt) Max with UCL. Environmental factors in the form of natural conditions and human factors, specifically the shift change that affects measurement results, are the factors causing the data to become out of control. The results of the process capability calculation obtained with precision are good, but the accuracy still needs to be improved.

Keywords: water, quality control, control chart, MEWMV, process capability.

1. INTRODUCTION

Various human activities, such as industry, hospitals, hotels, trade, offices, and education, always necessitate large amounts of water. The amount of water required for each of these activities varies, and the quality requirements vary depending on the activity. With the growth of the community's population and economic activities, so has the demand for water, both in quantity and quality(Suprihatin, S., Suparno, 2013). The demand for clean water is growing faster than the ability to supply it, so the proportion of the population that can be served by PDAMs is shrinking. As a result, the provision of clean water frequently prioritizes quantity (adequacy) over maintaining high quality. This frequently leads to the issue of wide variations in water quality. The Tirta Je'ne'berang Regional Drinking Water Company, Gowa Regency, is authorized to provide community drinking water services that meet the requirements. The Tirta Je'ne'berang Regional Drinking Water Company has a laboratory that measures and researches the quality characteristics used as a determinant of water quality, which include color, turbidity, the amount of dissolved solids, organic substances, and manganese. Conditions that occur in the community occasionally complain about the quality of the company's water, such as a cloudy color, smells, and has a high level of solids. This condition causes various variations in these qualities(Ariani Wahyu Dorothea, 2004).

Process capability is an analysis of variability that relates to product requirements or specifications as well as to production development in order to reduce or eliminate some of the ongoing variability. This process capability is a critical performance dimension that demonstrates the process's ability to produce in accordance with product specifications determined by management based on customer needs and expectations(Gaspersz, 2022). Process capability analysis definition is a critical component of the overall quality improvement system. Data from process capability analysis can be used to estimate how well a process will meet criteria, to aid product development in selecting or changing processes, and to reduce variability in the manufacturing process(Hardjosoedarmo, 1996). This process capability measurement is performed after the process is deemed to be under control, implying that the variations observed are solely due to natural factors. This process capability demonstrates how far a process can meet the desired specifications. In other words, machines and equipment with more reliable process capabilities will be required to meet tighter specifications. Multivariate capability analysis is one of the process capability analysis techniques. In order to use multivariate process capability analysis, the multivariate control chart must be under control and the multivariate assumption must also be met(Kurnia et al., 2013).

A control chart is a tool used in quality control to precisely describe what is meant by statistical control, and it can be used in a variety of ways. If one or more points in the control graph fall outside the control limit or show a non-random pattern, the control graph displays an uncontrollable state(Montgomery, 2009). A multivariate control chart is one of the control charts that can be used to control quality. A multivariate control chart for quality control is used when more than one interconnected quality dimension is involved. One type of multivariate control chart is the Multivariate Exponentially Weighted Moving Variance (MEWMV), which is a multivariate control chart with individual observations to detect changes in process variability involving weighting values (λ), smoothing constant (ω), and control limit width (L) which is proportional to the number of observed characteristics. This control chart has the advantage of being more sensitive to data shifts, so uncontrolled data will be detected more quickly. Furthermore, this control chart is resistant to the normal distribution. The MEWMV Control Chart was chosen because it is thought to be capable of detecting changes in the covariance matrix while assuming no shift in the process average.

Based on this description, the goal of this study is to determine the process capability by monitoring the water quality variability at PDAM Tirta Je'ne'berang using the Multivariate Exponentially Weighted Moving Variance (MEWMV) control chart. This study is expected to provide companies with information on statistical water quality control in the 2020 time frame.

2. RESEARCH

2.1. Multivariate Data

Multivariate analysis is a statistical method that analyzes several measurements (variables) on each object in one or more samples at the same time. According to this definition, multivariate analysis refers to any analytical technique that involves more than two variables at the same time(Dillon, 1984). Multivariate analysis is frequently confronted with the problem of observations made over time for p>1 variables or characters. The notation x_{ij} will be used to define the object i in the variable j. Multivariate data samples can be presented as follows(Richard A. Jhonson and Dean W. Wichern, 2007):

	Var-1	Var-2	$\cdots$	Var- j	$\cdots$	Var- p
Object-1	x_{11}	x_{12}	$\cdots$	x_{1j}	$\cdots$	x_{1p}
Object -2	x_{21}	x_{22}	$\cdots$	x_{2j}	$\cdots$	x_{2p}
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\cdots$	$\vdots$
Object- i	x_{i1}	x_{i2}	$\cdots$	x_{ij}	$\cdots$	x_{jp}
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\cdots$	$\vdots$
Object – n	x_{n1}	x_{n2}	$\cdots$	x_{nj}	$\cdots$	x_{np}

Alternatively, it can be written in the form of Matriks **X** as follows(Richard A. Jhonson and Dean W. Wichern, 2007):

$$X_{nxp} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2p} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{ip} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{np} \end{bmatrix} = \begin{bmatrix} x_1' \\ x_2' \\ \vdots \\ x_n' \end{bmatrix}$$

2.2. Multivariate Normality Test

Multivariate normal distributions are the main distributions and problems that arise in multivariate analysis. The term "multivariate normal" refers to an extension of "univariate normal." Among the assumptions that must be met are that data on independent variables have a multivariate normal distribution and that the covariance variance matrix is similar across groups or populations. As a result, a multivariate normality test is required to determine whether the data follows a multivariate normal distribution(Sharma, 1996). Calculating the distance measure of the mahalanobis in each observation and can be used to test the multivariate normal assumption. The following hypothesis will be used(Richard A. Jhonson and Dean W. Wichern, 2007):

H_0: Multivariate data is normally distributed.

H_1: Multivariate data are not normally distributed.

Furthermore, the multivariate normal testing procedure is carried out by plotting the Mahalanobis distance d_i^2 and the Chi-Square distribution ($3^2_{\frac{1}{n}(i-0,5),p}$). If H_0 is greater than 50% of the value of $d_i^2 \leq 3^2_{\frac{1}{n}(i-0,5),p}$, the data is said to have a multivariate normal distribution. H_0 is rejected if it is less than 50%.

2.3. Dependency Test

Independence testing is used to determine whether or not there is a relationship between two variables. If the correlation matrix between variables forms an identity matrix, the variables are said to be independent. The Bartlett test demonstrates that two or more groups of large sample data from a population with the same variance can be identified(Rencher, 2002). If the correlation matrix between variables $\mathbf{X_1, X_2, \ldots, X_p}$ forms an identity matrix, the variables are said to be independent. The Barlett Test is used to determine the relationship between the variables to be studied. The hypothesis will be used(Morrison, 1990):

H_0: $\mathbf{R = I}$ (no correlation between variables).

H_1: $\mathbf{R \neq I}$ (there is a correlation between variables).

With the following test statistics(Morrison, 1990):

$$3^2 = [n - 2 - \frac{2p+5}{6}] \ln |R| \tag{1}$$

As sunch, the decision to accept H_0 which means that between variables is independent if the value of $3^2 \leq 3^2_{(a,\frac{1}{2}p(p-1))}$, where n is the number of observations, p is the number of variables, **R** is the correlation matrix of each variable and $3^2_{(a,\frac{1}{2}p(p-1))}$ is the value of the Chi-Square distribution with a confidence level of and a degree of freedom of $\frac{1}{2}p(p-1)$.

2.4. Multivariate Exponentially Weighted Moving Variance (MEWMV)

MEWMV (Multivariate Exponentially Weighted Moving Variance) is a technique for detecting small changes in process variability. The MEWMV control chart is used to detect changes in the covariance matrix under the assumption that there is no change in the process average. The following equation yields the MEWMV control chart formulation(Huwang et al., 2007):

$$V_t = \omega(x_t - y_t)(x_t - y_t)' + (1 - \omega)V_{t-1} \tag{2}$$

Where m is the weighting value of $0 < m < 1$ $V_0 = m(x_1 - y_1)(x_1 - y_1)'$ with y_t being the estimated change in the average process of x_t which is defined in the following equation (Huwang et al., 2007):

$$y_t = \lambda x_t + (1-\lambda)y_{t-1} \tag{3}$$

Where $y_0 = 0$ and $0 < < 1$. If $t \geq p$ where t is the number of observations made. A matrix **C** is defined to determine the change in the covariance matrix. Matrix **C** is a t x t diagonal matrix with m as the smoothing constant element. Matrix **C** displays the V_t weighting value, which can be written as follows (Huwang et al., 2007):

$$\mathbf{C} = \begin{bmatrix} (1-\omega)^{t-1} & 0 & 0 & \square & 0 \\ 0 & \omega(1-\omega)^{t-2} & 0 & \square & 0 \\ 0 & 0 & \ddots & 0 & 0 \\ \vdots & \vdots & 0 & \omega(1-\omega) & \vdots \\ 0 & 0 & \square & 0 & \omega \end{bmatrix}$$

The following equation is derived from equation (2) (Huwang et al., 2007):

$$V_t = \sum_{i=1}^{t} \omega(1-\omega)^{t-i}(x_i - y_i)(x_i - y_i)' + (1-\omega)^t V_0 \tag{4}$$

Furthermore, the following equation is obtained for equation (3)(Huwang et al., 2007):

$$y_t = \sum_{j=1}^{t} \lambda(1-\lambda)^{t-j} x_j \tag{5}$$

Equation (5) is substituted into $x_i - y_i$ to yield the following new equation (Huwang et al., 2007):

$$\begin{aligned} x_i - y_i &= x_i - \sum_{j=1} \lambda(1-\lambda)^{t-j} x_j \\ &= x_i - [\lambda(1-\lambda)^{i-1}x_1 + \lambda(1-\lambda)^{i-2}x_2 \cdots + \lambda(1-\lambda)x_{i-1} + \lambda(1-\lambda)^0 x_i] \\ &= (1-\lambda)x_i - \lambda(1-\lambda)x_{i-1} - \cdots - 1 - \lambda)^{i-1}x_1 \end{aligned} \tag{6}$$

where i = 1,2,3,...,t. In matrix form, Equation (6) looks like this(Huwang et al., 2007):

$$(X - Y) = (I_t - M)X \tag{7}$$

Where I_t is an identity matrix with t x t dimensions and M is a lower triangular matrix with t x t dimensions and as a predetermined weight. Equation (4) can then be written as follows(Huwang et al., 2007):

$$\begin{aligned} V_t &= (X-Y)'C(X-Y) \\ &= X'(I_t - M)'(I_t - M)X \\ &= X'OX \end{aligned} \tag{8}$$

where **Q** is a t x t square matrix with the following equation(Huwang et al., 2007):

$$O = (I_t - M)'C(I_t - M) \tag{9}$$

The value of $tr(V_t)$ is obtained from equation (8) using the following equation(Huwang et al., 2007):

$$\begin{aligned} tr(V_t) &= tr(X'OX)' \\ &= tr(OXX') \end{aligned} \tag{10}$$

as a result of which the following equation is obtained(Huwang et al., 2007):

$$\begin{aligned} tr(V_t) &= \sum_{j=1}^{t} q_{1j} \left(\sum_{k=1}^{p} x_{1k} x_{jk}\right) + \sum_{j=1}^{t} q_{2j} \left(\sum_{k=1}^{p} x_{2k} x_{jk}\right) + \cdots + \sum_{j=1} q_{tj} \left(\sum_{k=1}^{p} x_{tk} x_{jk}\right) \\ &= \sum_{i=1}^{t} \sum_{j=1}^{t} q_{ij} \left(\sum_{k=1}^{p} x_{ik} x_{jk}\right) \end{aligned} \tag{11}$$

If the p value is 1, equation (11) becomes the EWMV equation, or it can be described as a controlled chart for univariate data. Meanwhile, if p is greater than one, the value of $E[tr(V_t)]$ is equal to the following equation(Huwang et al., 2007):

$$\begin{aligned} E[tr(V_t)] &= \sum_{i=1} q_{ii} E\left(\sum_{k=1}^{p} x_{ik}^2\right) + \sum_{i=1} \sum_{j'1}^{t} q_{ij} E\left(\sum_{k=1}^{p} x_{ik} x_{jk}\right) \\ &= p \sum_{i=1}^{t} q_{ii} = p.\,tr(O) \end{aligned} \tag{12}$$

Furthermore, in order to determine the control limit of $tr(V_t)$, the following values must be obtained(Huwang et al., 2007):

$$\begin{aligned}
Var[tr(V_t)] &= Var\left[\sum_{i=1}^{t} q_{ii}\left(\sum_{k=1}^{p} x_{ik}^2\right) + 2\sum_{i=1}^{t}\sum_{j<i}^{t} q_{ij}\left(\sum_{k=1}^{p} x_{ik}x_{jk}\right)\right] \\
&= \sum_{i=1}^{t} q_{ii}^2\, Var\left(\sum_{k=1}^{p} x_{ik}^2\right) + 4\sum_{i=1}^{t}\sum_{j<i}^{t} q_{ij}^2\, Var\left(\sum_{k=1}^{p} x_{ik}x_{jk}\right) \\
&= 2p\sum_{i=1}^{t} q_{ii}^2 + 4p\sum_{i=1}^{t}\sum_{j<i}^{t} q_{ij}^2 \\
&= 2p\sum_{i=1}^{t}\sum_{j=1}^{t} q_{ij}^2
\end{aligned} \quad (13)$$

Control limits can be determined for each t based on $tr(V_t)$ using the equation(Huwang et al., 2007):

$$E[tr(V_t)] \pm L\sqrt{Var[tr(V_t)]} \quad (14)$$

It can also be referred to as(Huwang et al., 2007):

$$\begin{aligned}
UCL &= p.tr(0) + L\sqrt{2p\sum_{i=1}^{t}\sum_{j=1}^{t} q_{ij}^2} \\
LCL &= p.tr(0) - L\sqrt{2p\sum_{i=1}^{t}\sum_{j=1}^{t} q_{ij}^2}
\end{aligned} \quad (15)$$

2.5. Capability Process

Process capability study is a method that combines statistical tools developed from normal curves and control charts with good technical judgment to interpret and analyze data representing a process. The purpose of the process capability study is to determine the distribution of variation and to determine the effect of time on the mean and distribution. Administration, analysis, and use of process capability studies should be an integral part of the quality engineering function(Wooluru et al., 2014). One of the most important components in process capability analysis is the Process Capability Ratio (PCR)(Montgomery, 2013). If the control chart is controlled and the assumptions are met, the process capability analysis can be performed by calculating the process capability index(Kotz, S. and Johnson, 1993). The capability index is used to determine whether or not a production process is capable(Bothe, 1997). If the Cp and Cpk values are greater than one, the production process is capable. The calculation of the Cp and Cpk indices for univariate data for statistically controlled data is as follows(Raissi, 2009):

$$C_p(X_i) = \frac{UCL_{X_i} - LCL_{X_i}}{6\sqrt{\sigma_{X_i}^2 + (\mu_{X_i} - T_{X_i})^2}} \quad (16)$$

$$C_{pk}(X_i) = min\left\{\frac{UCL_{X_i} - \mu_{X_i}}{3\sqrt{\sigma_{X_i}^2 + (\mu_{X_i} - T_{X_i})^2}}, \frac{\mu_{X_i} - LCL_{X_i}}{3\sqrt{\sigma_{X_i}^2 + (\mu_{X_i} - T_{X_i})^2}}\right\} \quad (17)$$

Furthermore, for multivariate calculations, the following equation can calculate all process capability indices(Raissi, 2009):

$$MC_p = \sum_{i=1}^{p} W_i C_p(X_i) \quad (18)$$

$$MC_{pk} = \sum_{i=1}^{p} W_i C_{pk}(X_i) \quad (19)$$

Where $MC_p$and MC_{pk} are multivariate C_p and C_{pk} respectively, and Wi are weights with magnitudes ranging from 0 to 1. The amount of weighting is determined by the level of importance of the quality characteristic variable, with the sum of the weights equal to one.

Meanwhile, for processes that are not statistically controlled, the process performance indices P_p and P_{pk} are used. For univariate data, the Pp and Ppk indices are computed as follows:

$$P_p = \frac{UCL - LCL}{6s} \quad (20)$$

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$$P_{pk} = min\{\frac{UCL-\bar{x}}{3s}, \frac{\bar{x}-UCL}{3s}\} \quad (21)$$

Multivariately, the P_p and P_{pk} process performance indices are appropriate because they do not take into account the weighting of each quality characteristic. For multivariate data, the P_p and P_{pk} indices are calculated as follows(Werner, 2011):

$$MP_p = (\sum_{i=1}^{p} P_p)^{\frac{1}{p}} \quad (22)$$

$$MP_{pk} = (\sum_{i=1}^{p} P_{pk})^{\frac{1}{p}} \quad (23)$$

3. Method

3.1 Data Sources and Research Variables

The data used in Secondary data from PDAM Tirta Je'ne'berang obtained in the IPA Pandang-Pandang laboratory for the period 2020, divided into two phases, were used. Phase I consists of data from January to June with the goal of determining the most optimal or sensitive weighting, and phase II consists of data from July to December with the goal of controlling the weights determined in phase I. Turbidity (X_1) and chlorine (X_2) are the variables used. Because the turbidity of the production water can affect the need for chlorine, the two variables interact. Chlorine can be used to remove turbidity from production water. Chlorine is used to purify water so that it does not emit unpleasant odors. The more turbid the production water, the more chlorine required, so the remaining chlorine in the production water will be significant.

3.2. Analysis Step

The following steps were taken in response to the research objectives:

1. Using descriptive statistics, describe water treatment data from PDAM Tirta Je'ne'berang Phase I.
2. Using PDAM Tirta Je'ne'berang Phase I water treatment data, test the multivariate normal distribution to see if the research variables follow the normal distribution.
3. Conducting independence testing on PDAM Tirta Je'ne'berang Phase I water treatment using the Bartlett test to determine whether the variables are correlated.
4. Using MATLAB software, analyze data from the PDAM Tirta Je'ne'berang Phase I water treatment data using the Multivariate Exponentially Weighted Moving Variance (MEWMV) control chart.
5. Repeat step 4 with the weights obtained from Phase II data.
6. Identify out-of-control data.
7. Conducting process capability analysis in phases I and II.

4. RESULTS

4.1 PDAM Tirta Je'ne'berang Phase I Water Quality Characteristics Description

The following table shows the average, standard deviation, variance, minimum value, and maximum value from PDAM Tirta Je'ne'berang Phase I water quality data for the period January to June 2020.

Table 1. Descriptive Statistics of PDAM Tirta Je'ne'berang Phase I Water Quality Characteristics

Variable	Minimum	Maximum	Mean	Std. Deviation	Variance	Specification
Turbidity	1,27	8,12	4,26	1,12	1,25	5 NTU
Chlorine	0,1	2,79	0,79	0,56	0,32	0,5 ppm

Based on Table 1, information about the water quality of PDAM Tirta Je'neberang Phase I is obtained. The average turbidity is 4.26 NTU, with a standard deviation of 1.12 indicating a level of spread to the average data and a variance of 1.25. The average chlorine concentration is 0.79, with a standard deviation of 0.56 and a variation of 0.32. This value indicates that the standard deviation has a small average or a narrow variance.

4.2 Multivariate Normality Test

The following table was obtained by performing an examination of the standard multivariate assumption on both turbidity and chlorine quality characteristics that must be met by calculating $d_i^2 = (X_i - \mu)'S^{-1}(X_i - \mu)$ compared to $3^2_{2;0,05}$:

Table. 2. d^2_i Calculation Results with $3^2_{2;0,05}$ Phase I

Observation	Turbidity	Chlorine	d_i^2	$3^2_{2;0,05}$
1	3,37	0,48	0,00663	5,9991
2	4,2	0,56	0,02202	5,9991
3	4,1	0,75	0,02301	5,9991
4	5,25	0,19	0,02874	5,9991
5	4,1	1,33	0,04721	5,9991
6	3,52	1,26	0,05279	5,9991
7	4,2	0,75	0,08112	5,9991
8	3,91	1,00	0,13766	5,9991
9	4,59	0,27	0,15333	5,9991
⋮	⋮	⋮	⋮	⋮
147	3,13	0,52	18,43322	5,9991

Based on Table 2, which was generated from 147 observational data, the proportion value of 0.9397 or 93.97%, indicates that the proportion value is greater than 50%, implying that the water quality characteristics of PDAM Tirta Je'ne'berang Phase I follow the multivariate normal distribution.

4.3 Dependency Test

The dependency test employs the Bartlett test to determine the correlation of the two variables with the following hypothesis:

H_0: **R = I** (no correlation between variables).

H_1**:** **R ≠ I** (there is a correlation between variables).

Based on the calculation results, $3^2 = 6,627 > 3^2_{0,05;1} = 3,842$ value is obtained at a significance level of 5% or 0.05, implying H_0 and concluding that the two Phase I water quality variables are correlated.

4.4 Monitoring Process Variability on Water Quality Phase I

A Multivariate Exponentially Weighted Moving Variance (MEWMV) control chart is used to monitor process variability in water quality control. MATLAB software is used to implement this control chart. $tr(V_t)$ is the point to be plotted on this control chart, and it necessitates the use of a **C** matrix to control changes in the covariance matrix. The **M** matrix is also a lower triangular matrix with elements. Following the completion of the various steps, the points will be plotted on the MEWMV control chart with predetermined control limits.

The results of Phase I data analysis using MATLAB software revealed that the MEWMV control chart began to be statistically controlled where there were no out of control points on the weights of =0.8 and =0.3 with L=4.8313. The value of $tr(V_t)$ Max on the weighting is 5.6778 with a value of UCL = 5.7147 and LCL = -0.0369. To determine the most optimum weighting on the MEWMV control chart, it is seen from the minimum difference from the $tr(V_t)$ value minus the statistically controlled UCL. The following table shows the difference between $tr(V_t)$ Max and UCL:

Table. 3. Result of lowering $tr(V_t)$ Max with UCL

ω	λ	L	$tr(V_t)$ Max	UCL	$tr(V_t)$ Max -UCL	Out Of Control
0,8	0,3	4,8313	5,6778	5,7147	-0,0369	0
0,8	0,4	4,8313	4,1714	4,1985	-0,0271	0
0,8	0,8	4,8063	0,4635	0,4645	-0,0010	0
0,8	**0,9**	**4,8004**	**0,1159**	**0,1160**	**-0,0001**	**0**
0,9	0,3	4,8900	6,6778	5,7722	0,9056	0
0,9	0,4	4,8950	4,1714	4,2444	-0,0730	0
0,9	0,8	4,8638	0,4635	0,4691	-0,0056	0
0,9	0,9	4,8475	0,1159	0,1167	-0,0008	0

According to table 3, the weighting of m =0.8 and λ =0.9 with L=4.8004 has the smallest difference. As a result, the fastest weighting m =0.8 and λ =0.9 are the most sensitive in detecting out of control data. Here's an example of a control chart for the weights m =0.8 and λ =0.9:

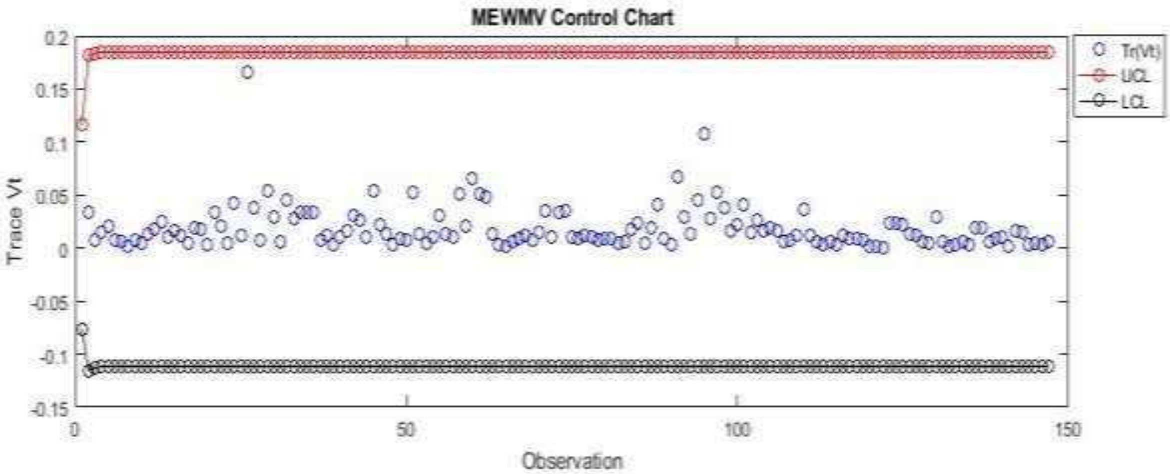

Fig 1. MEWMV Data Plot Control Chart Phases I with Weighted $m = 0,8$ and $\lambda = 0,9$ with $\mathrm{L} = 4,8004$

4.5 Monitoring Process Variability on Water Quality Phase II

The optimum weighting from phase I is used in the MEWMV control chart to control the variability of the phase II process. The results of the analysis of the process variability control of PDAM Tirta Je'ne'berang water quality phase II using the MEWMV control chart are as follows.

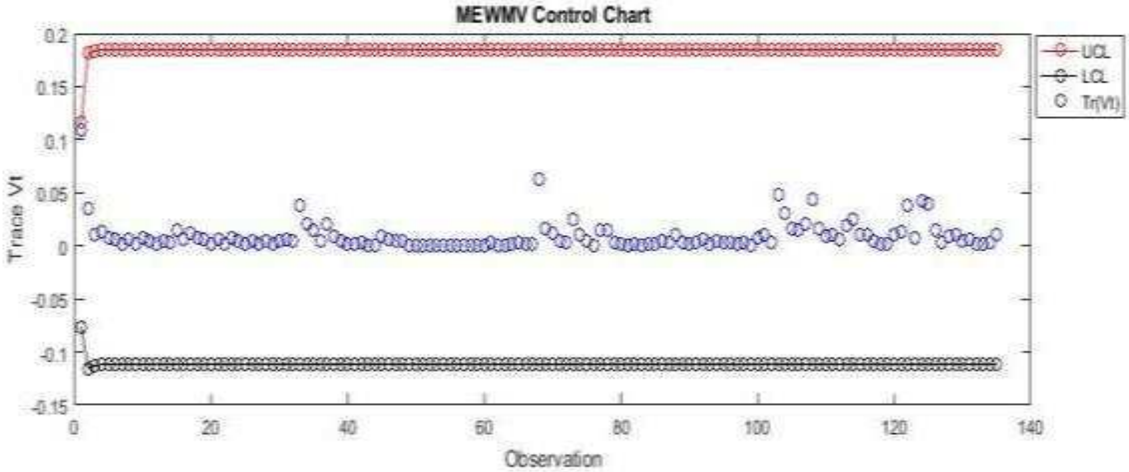

Fig 2. MEWMV Data Plot Control Chart Phases II with Weighted $m = 0,8$ and $\lambda = 0,9$ with $\mathrm{L} = 4,8004$

Figure 2 shows that the control of process variability in phase II is the same as in phase I, with the exception that the data is statistically controlled using the optimum weighting of phase I, this is indicated by the absence of points that are outside the control limits.

4.6 Identify Out Of Control Data

According to information obtained from the PDAM Tirta Je'ne'berang laboratory team, the factors for the Out Of Control data were caused by environmental and human factors. Environmental factors include erratic weather patterns that affect water clarity and inconsistent chlorine use. The human factor is caused by inconsistencies in measuring as well as shift changes, resulting in differences in measurement methods. The results of the causative variable identification show that the turbidity variable has a significant influence on the presence of Out Of Control data. This is due to the fact that the turbidity of the water is affected by the weather conditions at the time of measurement.

4.7 Conducting Process Capability Analysis in Phases I and II

The purpose of this process capability analysis is to determine the performance of a process as a whole on water quality data of PDAM Tirta Je'neberang which had previously been statistically controlled using the MEWMV control chart with attention to the level of precision and accuracy. The capability calculation is univariate, which means it is performed on each measure of water characteristics, namely turbidity and chlorine. More information is provided in the table below:

Table. 4. Univariate Process Capability

Variable	Phase I		Phase II	
	Cp	**Cpk**	**Cp**	**Cpk**
Turbidity	1,38	1,21	1,40	1,00
Chlorine	0,90	0,46	1,42	0,57

Table 4 shows that the values of Cp and Cpk were always greater than one on the turbidity variable. Meanwhile, the Cp and Cpk values of the independent chlorine variable were less than 1. The univariate calculation of process capability revealed that the turbidity variable had a high level of precision and accuracy. Meanwhile, the independent chlorine variable has poor process capability or performance, resulting in low precision and accuracy. After obtaining the capability value univariately, search for the capability value multivariately. The results of the multivariate process capability calculation are shown in the table below:

Table. 5. Multivariate Process Capability

Phase I		Phase II	
MCp	**MCpk**	**MCp**	**MCpk**
1,14	0,84	1,41	0,79

According to table 5, the multivariate capability calculation results show that the MCp value is greater than one and the MCpk value is less than one for both phases, indicating that the water quality at PDAM Tirta Je'ne'berang has good process performance but lower process accuracy. As a result, the company should pay attention to it.

5. CONCLUSIONS

Based on the findings of the analysis, it is concluded that the water quality at PDAM Tirta Je'neberang in Phase I for the period January to June 2020 has a multivariate normal distribution and a correlation for both variables. The MEWMV control chart was used to monitor process variability in Tirta Je'ne'berang Phase I water quality with weights ω=0.8, λ=0.9, and L=4.8004, demonstrating that there is no out of control data and that the data is statistically controlled. The weighting ω=0.8 and λ=0.9 is the most effective in detecting out-of-control process variability. The best weighting from Phase I is then used to detect variability in Phase II data. The MEWMV control chart analysis in Phase II found no out of control data from July to December, indicating that the data was statistically controlled. Environmental and human factors are the primary causes of data that is out of control. Environmental factors such as erratic weather that affects water clarity and inconsistent chlorine use are examples of environmental factors. The human factor is caused by a shift change, which results in differences in the measurement method. The identification result demonstrates that in the presence of out of control data, the turbidity variable is the most important factor. The precision of the PDAM Tirta Je'ne'berang water quality process is good, but the accuracy is still poor. This can be taken into account by PDAM Tirta Je'ne'berang when improving processes to achieve stability and capability.

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