Autocorrelated Multivariate Control Chart in Cooking Oil Industry

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ABSTRACT

In this article will be discussed about the implementation of control chart in cooking oil industry. Cooking oil has some parameters of quality i.e. Free Fatty Acid (FFA), Peroxide Value (PV), Iodine Value (IV), color (Red and Yellow), Moisture Content, Cloud Point (CP), Cloud Stability (CS) and Freezing Point. The observed data of cooking oil quality parameters shows that the data is autocorrelated. Therefore, residual mapping based on forecasting results from the time series model is used to construct autocorrelated multivariate control chart. In the multivariate T^2 Hotelling control chart of the residual VAR model (2) for chemical factor has a upper control limit (UCL) value of 22.18 and a median of 3.60. The T^2 Hotelling control chart of the residual VAR model (2) for physical factors has a control upper control limit (UCL) of 21.59 and a median value of 3.63.

Keywords
quality control, multivariate control chart, autocorrelated.

1. Introduction

Quality becomes the main factor of consumer decisions to get a product, consumers tend to buy a product from a company which is considered more qualified than its competitors. There are several ways to improve product quality, one of them is to apply statistical process control (SPC). Shewhart (1931) developed statistical process control (SPC) techniques for the improvement and assurance of product and service quality. Statistical process control (SPC) is a methodology used for monitoring and reducing the variation in manufacturing processes and the main tools of SPC are control charts. Normally, SPC works under the assumption that observed data is independent. However, the advanced measurement technology, shortened sampling interval and the nature of processes, especially in continuous processes, e.g., chemical processes, the independence of each observation has been violated in many scenarios. The lack of independence among each sample usually comes in the form of serial autocorrelation (Kandananond, 2014). There are many situations in which the simultaneous monitoring or control of two or more related quality characteristics is necessary. Lu and Reynolds (1999) and Jarrett and Pan, (2007) studied quality control chart for monitoring multivariate autocorrelated control chart. Monitoring two or more quality characteristics independently can be very misleading. Process-monitoring problems in which several related variables are of interest are sometimes called multivariate quality-control (or process-monitoring) problems. The original work in multivariate quality control was done by Hotelling (1947) (Montgomery, 2009).

Cooking oil has some parameters of quality i.e. Free Fatty Acid (FFA), Peroxide Value (PV), Iodine Value (IV), color (Red and Yellow), Moisture Content, Cloud Point (CP), Cloud Stability (CS) and Freezing Pointt. Free Fatty Acid (FFA) is a parameter to determine free fatty acid content in a sample. In FFA analysis, Phenolphthalein (PP) indicator is used. FFA value in pure CPO is below 3%. Peroxide Value (PV) is a parameter to know the oxidation rate of oil. PV is calculated as millilitre of Sodium Tiosulfate which is used to bind free Iodine in every gram of oil. The greater the PV, the more oxidation occurs in the oil. The size of the PV will affect the quality of oil. Iodine Value (IV) is a parameter for measuring clarity in cooking oil. Cooking oil clarity is indicated by the number of double bonds contained. Color is a visual analysis used to measure the color of fats and oils using the Lovibond Tintometer. Cloud Point (CP) is a parameter used to find out the temperature when the oil is cloudy or obfuscated.

2. T^2 Hotelling Control Chart

In 1947, Harold Hotelling introduced a control chart that could map a multivariate observation known as the T^2 Hotelling control chart. The calculation of T2 Hotelling's control chart for data with individual observations can be done using equation 2.1.

$$T^2 = (x - \bar{x})' S^{-1} (x - \bar{x}) \tag{2.1}$$

Where S^{-1} is the inverse of the covariant variant matrix and x is the average vector. Calculation of variance and covariance matrix can be done by using equation 2.2.

$$S = \frac{1}{2} \frac{V'V}{(m-1)} \tag{2.2}$$

Where m is the amount of data and V can be calculated using equation 2.3.

$$V_i = x_{i+1} - x_i \quad i = 1,2,\dots,m-1 \tag{2.3}$$

Calculations for upper control limits (UCL) can be performed using equation 2.4 and lower control limits (LCL) using equation 2.5.

$$UCL = \frac{(m-1)^2}{m} \beta_{\alpha, \frac{p}{2}, \frac{(m-p-1)}{2}} \tag{2.4}$$

$$LCL = 0 \tag{2.5}$$

3. Model *Vector Autoregressive*

The VAR model is a quantitative forecasting approach that is usually applied to multivariate time series data. This model explains the interrelationships between observations on particular variables at a time with observations on the variables themselves at previous times and also their association with observations on other variables at earlier times (Wei, 2006). The general form of VAR is : (Hamilton, 1994)

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + e_t$$

$$y_t = c + \emptyset(B) y_t + e_t \tag{2.6}$$

Where
$y_t = (y_{1,t}, y_{2,t}, \dots, y_{m,t})'$ is a variable vector of y sized (mx1)
$c = (c_1, c_2, \dots, c_m)'$ is a constant vector of size (mx1)
$e_t = (e_{1,t}, e_{2,t}, \dots, e_{m,t})'$ is a error vector of size (mx1)
$\emptyset$ = coefficient of var model, matrix (mxm)
$t = 1,2,\dots,n$
B = *backshift operator*
m = number of variables
p = order VAR
assumed $e_t \sim$ IIDN $(0, \Omega)$dan $E(e_t e_t)$=Ω.

The VAR model in equation (2.9) if translated to four variables and autoregressive order p becomes

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \\ y_{4,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ c_4 \end{bmatrix} + \begin{bmatrix} \emptyset_{1.11} & \emptyset_{1.12} & \emptyset_{1.13} & \emptyset_{1.14} \\ \emptyset_{1.21} & \emptyset_{1.22} & \emptyset_{1.23} & \emptyset_{1.24} \\ \emptyset_{1.31} & \emptyset_{1.32} & \emptyset_{1.33} & \emptyset_{1.34} \\ \emptyset_{1.41} & \emptyset_{1.42} & \emptyset_{1.43} & \emptyset_{1.44} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \\ y_{4,t-1} \end{bmatrix} + \begin{bmatrix} \emptyset_{2.11} & \emptyset_{2.12} & \emptyset_{2.13} & \emptyset_{2.14} \\ \emptyset_{2.21} & \emptyset_{2.22} & \emptyset_{2.23} & \emptyset_{2.24} \\ \emptyset_{2.31} & \emptyset_{2.32} & \emptyset_{2.33} & \emptyset_{2.34} \\ \emptyset_{2.41} & \emptyset_{2.42} & \emptyset_{2.43} & \emptyset_{2.44} \end{bmatrix} \begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \\ y_{3,t-2} \\ y_{4,t-2} \end{bmatrix} + \cdots$$

$$+ \begin{bmatrix} \emptyset_{p.11} & \emptyset_{p.12} & \emptyset_{p.13} & \emptyset_{p.14} \\ \emptyset_{p.21} & \emptyset_{p.22} & \emptyset_{p.23} & \emptyset_{p.24} \\ \emptyset_{p.31} & \emptyset_{p.32} & \emptyset_{p.33} & \emptyset_{p.34} \\ \emptyset_{p.41} & \emptyset_{p.42} & \emptyset_{1.43} & \emptyset_{p.44} \end{bmatrix} + \begin{bmatrix} y_{1,t-p} \\ y_{2,t-p} \\ y_{3,t-p} \\ y_{4,t-p} \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \\ e_{4,t} \end{bmatrix}$$

4. Identification Model VAR

In principle, the identification of the time series multivariate model is almost identical to the univariate model of time series. The identification of the VAR model is based on the pattern or structure of the sample correlation matrix (MACF) matrix and the partial sample correlation function matrix (MPACF) after a precise transformation has been performed to stabilize the variant, or differencing to stabilize the mean. There is another way to determine the corresponding VAR order, in addition to looking at the MPACF pattern also consider the value of Akakike Information Criterion (AIC). A model is said to be better if its AICp value is the minimum. The equation to calculate AICp or AIC value on VAR (p) is

$$AIC_p = \ln\left(\left|\hat{\Omega}_p\right|\right) + \frac{2pm^2}{(n-p)} \tag{2.7}$$

With $\hat{\Omega}_p$ is the residual covariance matrix VAR order *p*.

5. Diagnostic test of VAR model

The diagnostic test can be divided into two parts, namely the parameter significance test and the model conformity test (consisting of multivariate white noise assumption assay and the normal multivariate distribution of the residual).

a. Significance test

A good VAR model is a model whose parameters are significant, or the parameter values are different from zero. In general,if $\emptyset_{i,jk}$ is a parameter of VAR, *i*=1,2,...,*p* dan *j*=1,2,...,*m* and *k*=1,2,...,*m*.$\widehat{\emptyset}_{i,jk}$ is the estimated value of the parameter , and $SE(\widehat{\emptyset}_{i,jk})$ is the standard error of the estimated value $\widehat{\emptyset}_{i,jk}$, the parameter significance test can be done as follows

H_0: $\emptyset_{i,jk} = 0$ or VAR model parameter equal to zero

H_1: $\emptyset_{i,jk} \neq 0$ or VAR model parameter are not equal to zero

H_0 is rejected if the value of $\left| t_{hit} \right| > t_{\frac{\alpha}{2},df=n-M}$, with *M* = number of parameters or by using *p* (*p-value)*, is reject H_0 if *p-value* < α, with α is the level of significance error.

b. Test the suitability of model

The model conformity test includes model adequacy and assumption of the normal multivariate distribution of residuals.

1. Multivariate test White noise from residual.
   Multivariate tests White noise is to ensure the residuals of the model are not correlated with each other. The test used is Portmanteau test.
2. Test of Residual Assumption of Multivariate Distribution
   Assumptions to be met in VAR modeling are residuals that have a normal multivariate distribution. An examination of a normal multivariate distribution can be done by generating q-q plots of values :

$$d_t^2 = \left((\hat{e}_t - \bar{\hat{e}}_t)'\hat{\Omega}^{-1}(\hat{e}_t - \bar{\hat{e}})\right) t = 1, \dots, n \tag{2.8}$$

with

t	= t- observation
$\hat{e}_t$	= residual of each observation in the column vector
$\bar{\hat{e}}_t$	= residual average vector of each column
$\hat{\Omega}$	= residual covariance matrix
n	= number of variables

The hypothesis used is

H_0: normal multivariate distributed residuals

H_1: residuals are not normally multivariate distributed

H_0 fails to be rejected, if the value of $d_t^2 \leq \chi^2_{m;0,5}$ has a percentage over 50% of the amount data.

6. Methodology

Problem identification is done by observing the production process and visit several departments to collect information, mainly in the Quality Assurance department. After the problem information, hereinafter called problem formulation in this research is how to determine autocorrelated multivariate control chart on quality parameter of cooking oil. Furthermore, data is done in the Quality Assurance department to then performed data processing and data analysis. The data collected include data parameter of cooking oil. Test parameters of cooking oil in data processing are FFA, PV, IV, CP, and Color data (consist of Red and Yellow Color). After the data is collected, an autocorrelation test is performed and discarded on the data, followed by factor analysis to reduce the existing variables to less. After forming several factors, the formation of time series model where the residual result from time series model which then made multivariate map and will be analyzed.

7. Result and Discussion

7.1. Autocorrelation test

Autocorrelation test is used to know whether there is a correlation of each variable with time changes. The autocorrelation test of each variable can be seen visually through the graph plot ACF (Autocorrelation Function). If there is a lag line (the blue vertical line) that exceeds the significant limit (the red horizontal line) then it can be concluded that the data is autocorrelated. Graph of autocorrelation of test parameters of cooking oil can be seen in figure 1.

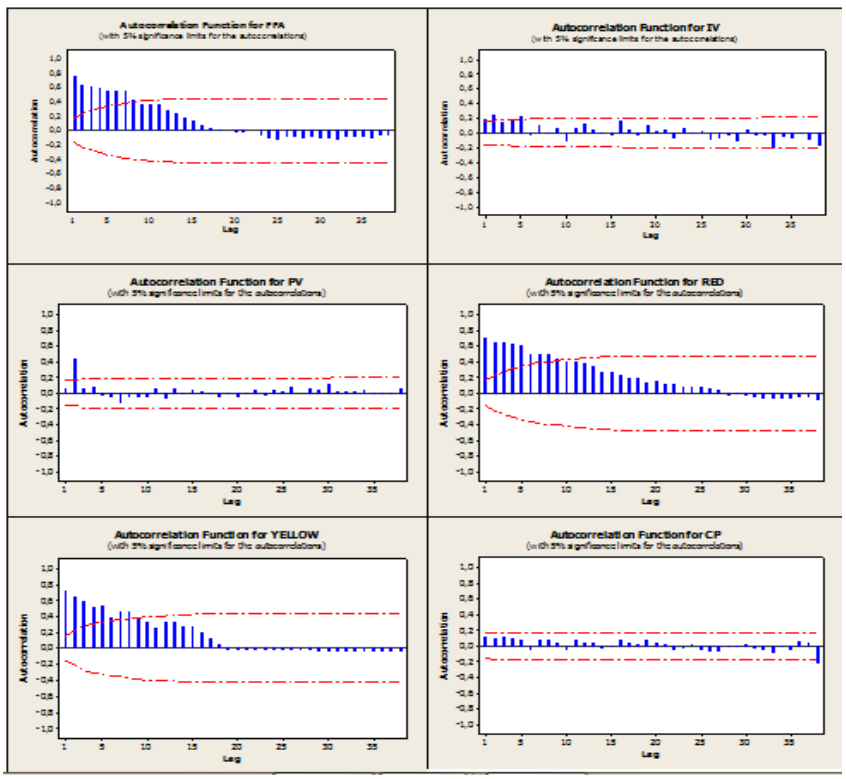

Figure 1. Plot ACF of six research variables

From the test results show that all parameters are autocorrelated. Thereby, the convention control chart is suitable to analyze the data. The data must be processed using VAR model.

7.2. Factor Analysis

Factor analysis test is conducted to see the number of factors formed from the overall parameter data. Factor analysis is a process an approach to find the relationship between a number of variables that are mutually independent one another so the number of initial variables can be grouped into several factors. The value of correlation between each variable with the factors formed can be seen in the component matrix table (**Table 1**) and rotated component matrix (**Table 2**).

Table 1. Component Matrix

Parameter	Component	
	1	2
FFA	,554	,509
IV	-,728	,517
PV	,239	-,456
Red	,790	,368
Yellow	,667	,409
CP	,757	-,475

Table 2. Rotated Component Matrix

Parameter	Component	
	1	2
FFA	,751	-,038
IV	-,231	-,863
PV	-,107	,503
Red	,843	,221
Yellow	,775	,110
CP	,280	,849

The matrix component from the rotation process shows a clearer distribution of variables. Grouping parameters to the factors is based on value of component in Table 2. The FFA parameter is grouped in factor 1 because the value component 1 (0,751) is larger than component 2 (0.038). Parameter IV is grouped in factor 2 because the value component 2 (0,863) is larger than component 1 (0.231). The FFA, IV, PV, Color Red, Color Yellow, and CP parameters have been grouped to 2 factors. Therefore the parameters are grouped into :

1. Physical factors consisting of parameters FFA, Color Red and Color Yellow.
2. Chemical factors consisting of parameters IV, PV and CP.

7.3. VAR Model for Chemical Factor

Model identification is performed to determine the appropriate VAR order. To determine the corresponding VAR order, it can be seen from the value of Akakike Information Criterion (AIC). The smaller the AIC value the more appropriate the model. From the AIC value of chemical factor it is known that the smallest AIC value refers to the VAR model (2) so as to select the VAR model (2) for the formation of the VAR model on the chemical factor. In **Table 3** we can see the VAR model parameters (2) chemical factors that have significant.
From the parameter of the VAR model significant, it can be formed into the equation of VAR model (2) as follows.

$$\begin{bmatrix} X_{2,t} \\ X_{3,t} \\ X_{6,t} \end{bmatrix} = \begin{bmatrix} 49{,}79605 \\ 0 \\ 10{,}46470 \end{bmatrix} + \begin{bmatrix} 0 & 2{,}41716 & -0{,}35637 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} X_{2,t-1} \\ X_{3,t-1} \\ X_{6,t-1} \end{bmatrix} + \begin{bmatrix} 0{,}22071 & 0 & 0 \\ 0{,}00179 & 0{,}41874 & 0 \\ -0{,}06075 & 0 & 0 \end{bmatrix} \begin{bmatrix} X_{2,t-2} \\ X_{3,t-2} \\ X_{6,t-2} \end{bmatrix}$$

The equations are further translated for each series

$X_{2,t} = 49{,}79605 + 2{,}41716\ X_{3,t-1} + -0{,}35637\ X_{6,t-1} + 0{,}22071\ X_{2,t-2}$
$X_{3,t} = 0{,}00179\ X_{2,t-2} + 0{,}41874\ X_{3,t-2}$
$X_{6,t} = 10{,}46470 + -0{,}06075\ X_{2,t-2}$

The model above shows that the model is a time series multivariate model. Where to forecast variable X_2 (IV) influenced by variable X_3 (PV) and variable X_6 (CP). Where to forecast variable X_6 (CP) also influenced by variable X_2 (IV). Furthermore, the model suitability test consisted of multivariate white noise test of residual and residual

assay test of normal multivariate distribution. From the model conformity test, it is known that the residual model VAR (2) chemical factor is not correlated with each other and residual also has multivariate normal distribution.

Tabel 3 Estimation of VAR Model Parameter (2) Chemical Factor

Equation	Parameter	Estimate	Standard Error	t Value	Pr > |t|
x2	**CONST1**	49.79605	5.06176	9.84	0.0001
	AR1_1_1	0.00000	0.00000		
	AR1_1_2	2.41716	1.10701	2.18	0.0307
	AR1_1_3	-0.35637	0.17770	-2.01	0.0468
	AR2_1_1	0.22071	0.07849	2.81	0.0056
	AR2_1_2	0.00000	0.00000		
	AR2_1_3	0.00000	0.00000		
x3	**CONST2**	0.00000	0.00000		
	AR1_2_1	0.00000	0.00000		
	AR1_2_2	0.00000	0.00000		
	AR1_2_3	0.00000	0.00000		
	AR2_2_1	0.00179	0.00023	7.81	0.0001
	AR2_2_2	0.41874	0.07298	5.74	0.0001
	AR2_2_3	0.00000	0.00000		
x6	**CONST3**	10.46470	1.45727	7.18	0.0001
	AR1_3_1	0.00000	0.00000		
	AR1_3_2	0.00000	0.00000		
	AR1_3_3	0.00000	0.00000		
	AR2_3_1	-0.06075	0.02373	-2.56	0.0115
	AR2_3_2	0.00000	0.00000		
	AR2_3_3	0.00000	0.00000		

7.4. VAR Model for Physical Factor.

VAR model identification for physical factor has the same step as VAR model for chemical factor. To determine the corresponding VAR order, it can be seen from the value of Akakike Information Criterion (AIC). A model is better if the AIC value is minimum. From the AIC value of physical factors it is known that the smallest AIC value refers to the VAR model (2) so as to select the VAR model (2) for the formation of the VAR model on the physical factor. **Table 4** shows the VAR model parameters (2) significant physical factors.

Tabel 4 Estimation of VAR Model Parameter (2) Physical Factor

Equation	Parameter	Estimate	Standard Error	t Value	Pr > |t|
x1	**CONST1**	0.01616	0.00398	4.06	0.0001
	AR1_1_1	0.22051	0.09431	2.34	0.0216
	AR1_1_2	0.00000	0.00000		
	AR1_1_3	0.00000	0.00000		
	AR2_1_1	0.28860	0.09436	3.06	0.0029
	AR2_1_2	0.00000	0.00000		
	AR2_1_3	0.00014	0.00006	2.36	0.0206
x4	**CONST2**	0.50064	0.13476	3.72	0.0004
	AR1_2_1	0.00000	0.00000		
	AR1_2_2	0.36782	0.08481	4.34	0.0001
	AR1_2_3	0.00000	0.00000		
	AR2_2_1	0.00000	0.00000		
	AR2_2_2	0.34222	0.08506	4.02	0.0001
	AR2_2_3	0.00000	0.00000		
x5	**CONST3**	8.19033	2.05286	3.99	0.0001
	AR1_3_1	0.00000	0.00000		
	AR1_3_2	0.00000	0.00000		
	AR1_3_3	0.40271	0.10104	3.99	0.0001
	AR2_3_1	0.00000	0.00000		
	AR2_3_2	0.00000	0.00000		
	AR2_3_3	0.21251	0.10110	2.10	0.0383

From the parameter of the VAR model significant, it can be formed into the equation of VAR model (2) as follows.

$$\begin{bmatrix} X_{1,t} \\ X_{4,t} \\ X_{5,t} \end{bmatrix} = \begin{bmatrix} 0{,}01616 \\ 0{,}50064 \\ 8{,}19033 \end{bmatrix} + \begin{bmatrix} 0{,}22051 & 0 & 0 \\ 0 & 0{,}36782 & 0 \\ 0 & 0 & 0{,}40271 \end{bmatrix} \begin{bmatrix} X_{1,t-1} \\ X_{4,t-1} \\ X_{5,t-1} \end{bmatrix} + \begin{bmatrix} 0{,}28860 & 0 & 0{,}00014 \\ 0 & 0{,}34222 & 0 \\ 0 & 0 & 0{,}21251 \end{bmatrix} \begin{bmatrix} X_{1,t-2} \\ X_{4,t-2} \\ X_{5,t-2} \end{bmatrix}$$

The equations are further translated for each series

$X_{1,t} = 0{,}01616 + 0{,}22051\ X_{1,t-1} + 0{,}28860\ X_{1,t-2} + 0{,}00014\ X_{5,t-2}$
$X_{4,t} = 0{,}50064 + 0{,}36782\ X_{4,t-1} + 0{,}34222\ X_{4,t-2}$
$X_{5,t} = 8{,}19033 + -0{,}40271\ X_{5,t-1} + 0{,}21251\ X_{5,t-2}$

The model above shows that the model is a time series multivariate model to forecast variable X_1 (FFA) is influenced by variable X_5 (Color Yellow). Furthermore, the model suitability test consisted of multivariate white noise test of residual and residual test of normal multivariate distribution. From the model conformity test, it is known that the residual model VAR (2) physical factors are not correlated with each other and the residual has also multivariate normal distribution.

7.5. Residual Multivariate control chart VAR Model for Chemical Factor

The residuals of the VAR model (2) for chemical factors that have been proven independence and the multivariate normal distribution are further compiled into control charts which can be seen in **Figure 2**

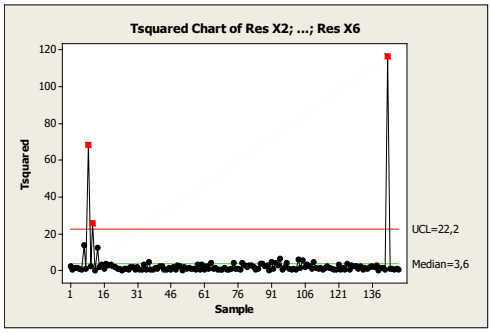

Figure 2. Residual Multivariate Control Chart Chemical – First Iteration

Figure 2 shows that a multivariate control chart that has been formed for chemical factors still has residuals out of control limits. Furthermore, residuals out of the control limits may be disposed of in order to obtain fully in-control residuals.

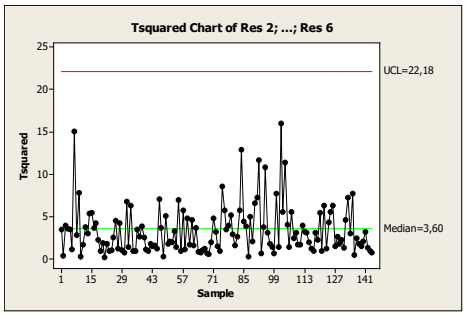

Figure 3. Residual Multivariate Control Chart Chemical factor under in control condition

Figure 3 shows the residual multivariate control chart of chemical factors that have been in full in control condition with a limit of Upper Control Limit (UCL) of 22.18 and a median of 3.60.

7.6. Residual Multivariate control chart VAR Model for Physical Factor

The residuals of the VAR model (2) for chemical factors that have been proven independence and the multivariate normal distribution are further compiled into control charts which can be seen in Figure 4.

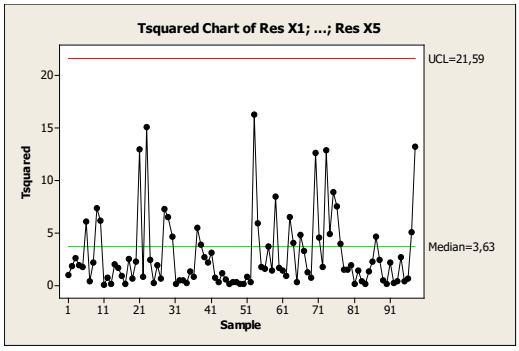

Figure 4. Residual Multivariate Control Chart Physical factor under in control condition

Figure 4 shows the residual multivariate control chart of physical factors that have been in full in control condition with a 21.59 Upper Control Limit (UCL) limit and a median value of 3.63.

8. Conclusion and Suggestions

Some of the quality parameters used in this study are FFA, IV, PV, color red, yellow color, CP. From the results of research conducted, it is known that the quality parameters of cooking oil are correlated and autocorrelated each other. Therefore, the appropriate control chart to be used is the T^2 Hotelling multivariate control chart of the residual time series model. Factor analysis is conducted to form quality parameters into two factors, namely physical factors and chemical factor. Physical factors consist of parameter FFA, color red, color yellowr. Chemical factor consist of parameter IV, PV, and CP. From the formation of time series model for physical factors and chemical factors it is known that the model corresponding to each factor is VAR (2) model. T^2 Hotelling multivariate control chart from residual model VAR (2) for chemical factor has upper control limit (UCL) of 22,18 and median value 3,60. The T^2 Hotelling control chart of the residual VAR model (2) for physical factors has a control upper limit (UCL) of 21.59 and a median value of 3.63. T^2 Hotelling multivariate control chart from the residual VAR model to control the quality of cooking oil with correlated and autocorrelated quality parameters.

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