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We appreciate your submission to the ***Mathematical Modelling of Engineering Problems*** (***MMEP***) and have completed the review process for your manuscript titled " **Auto-correlated Multivariate Quality Control for Electronic Products Manufacturing with Decomposition Analysis."**

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Auto-correlated Multivariate Quality Control for Electronic Products Manufacturing with Decomposition Analysis

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ABSTRACT

The majority of modern industrial processes outcomes are of multivariate. Univariate control charts can lead to misleading conclusions in the case high correlation among variables. This paper presents a novel multivariate statistical process control to monitor electronic products with multivariate correlated outcomes. We develop a procedure for monitoring multivariate auto-correlated data by multivariate autoregressive (MAR) model using neural network. This study investigates the significance and sensitivity in the use of MCUSUM, MEWMA and T^2 Hotelling to detect small changes in the mean vector of a process. The identification of out-of-control signals generated from multivariate statistical process control is derived from univariate charts and decomposition approach. The proposed decomposing statistics determines the contribution of variables in out-of-control signals by T^2 Hotelling multivariate control charts. Further, MCUSUM and MEWMA control charts have good run length performance and are sensitive to detect small changes in the process's mean vector, which enables fast action.

1. INTRODUCTION

The requirements of product inspection have become more challenging as the product attributes becomes complex and increasingly correlated over time. Since variability is a major signal of poor quality, statistical process monitoring is a tool of quality control [1]. Statistical process monitoring (SPM) in many continuous flows of the electronic product manufacturing industry usually evolves over time to deal with auto-correlated, multivariate quality data. An efficient SPM system can rapidly detect changes in a process that may result from uncontrollable and unpredictable causes.

While traditional control charts assumed that the process is independently distributed over time, this assumption is violated with the advances in electronic product manufacturing. The existence of autocorrelation results in the creation of control charts for variables being in violation of one of the main assumptions, namely serial-sample independence. The breaching presumption of independence affects both the Average Run Length (ARL) of the control charts and renders them unstable [2]. In addition, too many false alarms may be detrimental because an incorrect source of variation may be misidentified and/or the process engineer tends to disregard the control charts altogether. It can thus explain the relatively low use of control charts on continuous-flow systems [3].

SPM is also facing multivariate problem because the product quality of the electronic product manufacturing industry usually is determined by several interrelated quality attributes/variables [4]. Interrelated between variables has a major impact on the statistical properties of traditional control charts and can lead to a significant increase in the average false alarm rate and a decrease in the ability to detect process changes. While applying univariate control charts to each of variables, this approach can mislead quality decisions. Therefore, multivariate based quality control methods is required to consider those variables simultaneously.

The present study will address the auto-correlated, multivariate quality control for electronic product manufacturing. We propose a model based on ANN to predict and build the residual based control chart for multivariate data with autocorrelation order p (AR(p)) processes.

The rest of this paper is organized as following. Section 2 discusses relevant literature review, such as SPM of multivariate auto-correlated observations, multivariate control chart, and ANN for multivariate and auto-correlated observations. Section 3 details the research methodology including manufacturing process and research variables. Section 4 illustrates a practical application and discussion. Finally, conclusions are provided in Section 5.

2. LITERATURE REVIEW

2.1. Multivariate auto-correlated control charts

Autocorrelation occurs in most of the continuous and batch operation process [5] and its solution is constantly searched. Loredo [6] presented a method for monitoring auto-correlated processes based on regression adjustment. Psarakis & Papaleonida [7] suggest that even small levels of autocorrelation can have a major impact on the statistical properties of traditional control charts and can lead to a significant increase in the average false alarm rate and a decrease in the ability to detect process changes. One approach to dealing with the problem of autocorrelation is to filter out autocorrelation by a time series model and use residuals for control. Besides that, the residuals would be statistically uncorrelated if the time series model is accurate.

Assumptions in standard quality control then will be reached and a conventional control chart can be used. Callao and Rius [8] demonstrated that residual control charts provide the device behavior over time and efficient detection capabilities using an AR(1). Many methods are available for the monitoring and control of multivariate systems by an extension of the univariate case. According to Khediri & Mohamed [9], the use of multivariate autoregressive (MAR) models is made in the presence of a multivariate method, characterized by a serial correlation between various variables, measurement, and monitoring of the system. Their research proposed an MAR control chart for multivariate auto-correlated processes. For an MAR process with *m* variables, it is denoted by $\mathbf{x_t} = (\mathbf{x_{1t}}, \mathbf{x_{2t}}, \ldots, \mathbf{x_{mt}})$ as a $(m \times 1)$ vector.

Psarakis and Papaleonida [7] mentioned that once a shift is observed in the mean and/or variance of the residuals process, it is assumed that the mean and/or variance of the process itself has changed. Plotting the residuals on a control chart thus provides a mechanism for detecting a shift in a process. The logic of using residual charts is that the residuals will be distributed random variables independently and identically if the correct time series model is applied to the data. Then all the requirements of conventional quality control will be fulfilled, and any of the traditional SPC charts can be used. Therefore, the construction of time series model for multivariate auto-correlated data becomes very important in statistical process control with multivariate auto-correlated data processes. Traditionally, the ARIMA model was one of the most used linear models of time series prediction. The ARIMA model, however, cannot easily capture the nonlinear patterns.

To resolve the autocorrelation issue, researchers seek for solutions. Alwan and Roberts [10] introduced an approach to deal with autocorrelation in creating of control chart by using residual based control chart. Woodall and Faltin [11] reviewed the impact of self-correlation on control charts output and how to deal with autocorrelation. Several methods related to autocorrelation problems are developed, such as cumulative sum (CUSUM) control chart with autocorrelation data [12], [13], [14]. Further, researchers [15], [16], [17], and [18] also developed control charts with autocorrelation data by exponentially weighted moving average (EWMA) control chart.

Control charts with multivariable are studied in literature, such as T^2 Hotteling, multivariate cumulative sum (MCUSUM) control chart and multivariate exponentially weighted moving average (MEWMA) control chart [19], [20], [21], and [22]. Some researchers also developed improved control charts to deal with multivariate auto-correlated data, which related to multivariate data with time series effect [23], [24], [25], [26], and [27]. Jarrett and Pan [28] developed multivariate control charts for independent processes and univariate control charts for auto-correlated processes. Their research proposed a multivariate autoregressive (MAR) control chart for multivariate auto-correlated processes.

2.2. Residual control chart

2.2.1. T^2 Hotelling Control Chart

The multivariate extension of Shewart-type control chart is T^2 Hotelling's chart [5]. In 1947, Harold Hotelling introduced a control chart that could describe multivariate observations known as the T^2 Hotelling control chart. There are two versions of the T^2 Hotelling control map calculation, namely subgroup data and individual observation data. The well-established Shewart X-Chart is a simple, univariate statistics used to measure the process 's stability against large shifts. In terms of standard deviation, a large magnitude is defined statistically. Since residuals are assumed to have a zero mean and a σ_r standard deviation, an observation is considered in control when the target residual value r_i lies between the control limits defined by $\lambda\sigma_r$, where a given in-control run length property is determined by λ. Using the Mahalanobis distance [25] this chart reduces the residuals to a scalar. If Eq. 1 condition is met, an observation is assumed to be in-control.

$$T_i^2 = R_i^T \sum\nolimits_R^{-1} R_i \frac{m(n-1)}{n-m} F_{m;n-m;(\alpha)}; \text{ for } i = 1,2,\cdots,n \tag{1}$$

Where n is number of observations, m is the number of variables, R_i is the residual vector and $F_{m;n-m;(\alpha)}$ is Fisher distribution. The term α is the risk level and it ensures a desired in-control ARL or in-control rate of false alarm. $\sum_R^{-1} R_i$ is the inverse off the estimated residual covariance matrix.

2.2.2. Multivariate CUSUM control chart

The CUSUM chart was created to address the problem of Shewart and T^2-Hotelling control charts that are insensitive to moderate changes, since they use only the most recent observation details [9]. To detect minor process changes, CUSUM charts accumulate deviations from a given target in the residuals of previous observations. The most widely used CUSUM control procedure is Crosier's chart [29]. For $S_0 = 0$, where 0 is a 1× *m* matrix of zeros, the statistics is as follows,

$$S_i = \begin{cases} 0 & \text{, if } C_i \le k \\ (S_{i-1} + R_i)\left(1 - \dfrac{k}{C_i}\right) & \text{, otherwise} \end{cases} \tag{2}$$

$$C_i = (S_{i-1} + R_i)\Sigma_R^{-1}(S_{i-1} + R_i)^T \tag{3}$$

Crosier's chart signal a shift when $T_S^2 = S_i^T \sum_R^{-1} S_i$ overcomes a predetermined limit *H*. The CUSUM scheme indicates when the *S* statistics are greater than a certain level *H*. So that, if $S_i > H$, where does the chart indicate a change of process for a given in-control desired run length (RL) characteristic, *k* and *H* must be calculated beforehand.

Common practice in CUSUM procedures is to assume that sample size is equal to one. Multivariate CUSUM

(MCUSUM) statistic S_i allows to detect a specific shift in the process mean vector:

$$S_i = max\{S_{i-1} + a^T R_i - k, 0\} \quad (4)$$

where,

$$a^T = \frac{\delta_r^T \Sigma_r^{-1}}{\sqrt{\delta_r^T \Sigma_r^{-1} \delta_r}}$$

which δ_r is the residual mean vector and Σ_r is the variance-covariance matrix. An MCUSUM scheme cumulates deviations more than *k* units from the goal mean value. Hence, *k* serves as the reference value of the scheme. The control scheme signals an out-of-control situation when the value of S_i is greater than a certain pre-determined decision value *H* (Issam and Mohamed, 2008).

2.2.3. Multivariate EWMA control chart

Although CUSUM charts take all the previous measurements into account, EWMA charts the last observation weight based on its significance in characterizing the process. The greater the value of λ, the greater the last observation's effect [5]. The EWMA statistics are iteratively described as Eq. 5,

$$Z_i = (1-\lambda)Z_{i-1} + \lambda R_i \text{ ; for } i = 1,2,\cdots,n \quad (5)$$

where λ is diagonal matrix of value $0 \leq \lambda_j \leq 1$, $j = 1,2,\cdots,m$. The multivariate EWMA (MEWMA) scheme signals if the

$$T_Z^2 = Z_i^T \sum\nolimits_Z^{-1} Z_i \quad (6)$$

surpasses a predetermined value *H*, where H > 0 is chosen to achieve a specified in-control (on-target) ARL_0. The asymptotic form of the covariance matrix is $\Sigma_Z = \left(\frac{\lambda}{2-\lambda}\right)\Sigma_R$ [30].

Reynolds and Lu [31] investigated AR(1), AR(2) and ARMA(1,1) models for a residual X-chart and pointed out that the residual X-chart may lack the capacity to detect the mean shift of the processes. Those research, however, considered only for processes which has small order of *p* on autoregressive AR(*p*) model. Whereas real condition sometimes autocorrelation with high order (p > 5) are occurred. Besides that, multivariable with high autocorrelation also must considered in one time. This condition usually occurs in the manufacturing industry with mass production and fast flow production. Therefore, the general multivariate autoregressive (MAR) models should be developed to overcome multivariable and autocorrelation problem on statistical process monitoring using residual based multivariate control chart.

2.3. Applying ANN to SPM of multivariate auto-correlated observations

Artificial neural network (ANN) is an estimation tool for the output process (responses) [32]. Multi-layer perceptron (MLP) is a nonparametric estimator that can be used for classification and regression. A multilayer feed forward ANN with continuous output layer is suitable for regression problem.

If an AR(*p*) model follows the quality characteristics of an auto-correlated phase, the mean vector of each cycle is a function of the mean vectors of the previous *p* cycle. Consequently, the inputs of the desired ANN are the quality characteristics vectors of previous *p* periods, and the output will be the quality characteristics vector of the time we need to forecast. In the implementation process, to generate the forecasted vector in the output layer, we add the characteristics of the *p* preceding periods for each cycle to the network input layers. Arkat et al., [3] mentioned that vector of the residuals of that cycle is the difference between the forecasted and the actual values of the quality characteristics vectors of each period.

Over the last two decades, research in statistical process monitoring fields and practices applied machine learning to detect and diagnose faults of the industrial operation process and production results**.** In terms of data analysis in SPM, artificial neural network (ANN) has been applied since 1980s [3]. Some scholars studied ANN applications in univariate control chart, such as [33], [34], and [35]. ANN has also been applied to monitor multivariate processes, such as [36], [37], [38], [39], and [40]. Arkat et al [3] designed an ANN-based model to forecast and construct residual CUSUM chart for multivariate autoregressive of order one, AR(1), processes. Khediri et al. [5] proposed support vector regression to construct several control charts that allows monitoring of multivariate nonlinear auto-correlated processes.

2.4. Summary

There is a recurrent violation of independently distribution assumptions with the advance made in many automation processes such as electronic component manufacturing because the high selection of samples creates a set of observations that are close enough to be dependent. How to apply and evaluate control charts designed to account for autocorrelation is critical. Residual control charts provide a good understanding of the device behavior over time and efficient detection capabilities but does not fully fulfill the requirement of autocorrelation and multiple variates observations.

3. METHOD

This study aims to present a residual control chart using MAR model with ANN (MAR-ANN) to solve the SPM problem related to multivariate with auto-correlated observations. Moreover, this study makes diagnostic of out-of-control signal in multivariate control chart using decomposition technique. Comparison of multivariate control chart with univariate one is also conducted. Figure 1 shows the operational procedure of the proposed mothed. Multiple variables are defined as the quality parameter which correlate to each other, and each variable is of time series.

Correlation test is employed to know the strength of correlation between variables. In this study, correlation test determines the correlation between quality parameters of a product. If there is a correlation between quality parameters, then the control chart preparation is based on a multivariate control chart approach because it will involve more than one quality parameter in one chart. The hypothesis used in testing the correlation between quality parameters is as follows. To determine whether there is a correlation between quality parameters is based on the p-value.

H_0: $\rho = 0$ or there is no correlation
H_1: $\rho \neq 0$ or there is a correlation

In terms of autocorrelation, this study applies a method proposed by Loredo [6] for monitoring auto-correlated processes that showed the superiority of residual-based control charts in comparison with observation-based control charts when detecting the mean shift in short-run auto-correlated data processes. Each variable is examined by autocorrelation test to know whether each variable correlates with time changes. The autocorrelation test of each variable can be seen visually through the autocorrelation function (ACF) plot graph. Variables have a significant autocorrelation if there is a significant lag in the ACF plot. To overcome autocorrelation, time series modeling must be done, the model obtained calculates the model error to meet the assumption of white noise. The coefficient of autocorrelation lag k measures the correlation between values of each variable at time t and time t-k and shows the limit of probability around 0. If the autocorrelation graph is below the 95% likelihood limits at a certain lag, a large autocorrelation occurs at that lag.

Figure 1 presents a four-step procedure. First, data are checked for each variable by ACF and correlation between variables by Pearson's correlation. Second, MAR modelling process determines the model considering autocorrelation and multivariate. To estimate MAR, this research proposes an ANN with MLPRegressor approach. Third, residual white-noise checking is conducted to ensure all residual variables can be used for the multivariate control chart. White noise residual checking involves multivariate normality, independence and identical test. Then, fourth step builds a residual-based multivariate control chart where residual is the difference between actual value and estimated value based on the MAR model of each variable.

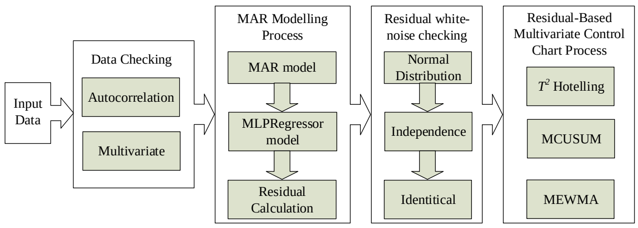


Figure 1. Procedure to build the proposed control chart

If the quality characteristics of an auto-correlated process follow an AR(p) model, the mean vector of each period is a function of the mean vectors of the previous p periods. The inputs of the desired ANN are therefore the quality characteristics vectors of the previous p periods and the output will be the quality characteristics vector of the period to forecast. Before forming the ANN, the MAR as time series for multivariate model is performed to determine the autoregressive order p for each factor.

Based on Khediri et al. [5], this study performs time series estimation for a multivariate process by MAR. Each input variable $Y_{(i=1,2,\dots,m)t}$ is defined by the previous variables of the series $(Y_{1(t-1)},\cdots,Y_{1(t-p)},\cdots,Y_{m(t-1)},\cdots,Y_{m(t-p)})$, where m is the number of variables and p is the lagged time. Supposed that we have an autoregressive process with m variables and order p that need to be estimated, one can present $Y_{(i=1,2,\dots,m)t}$ by Eq. 7:

$$Y_{(i=1,2,\dots,m)t} = f(Y_{1(t-1)},\cdots,Y_{1(t-p)},\cdots,Y_{m(t-1)},\cdots,Y_{m(t-p)}) \quad (7)$$

Estimation of the process using MAR model provides $\hat{f}$ which allows to predict $Y_{(i=1,2,\dots,m)t}$ as Eq. 8:

$$\hat{Y}_{(i=1,2,\dots,m)t} = \hat{f}(Y_{1(t-1)},\cdots,Y_{1(t-p)},\cdots,Y_{m(t-1)},\cdots,Y_{m(t-p)}) \quad (8)$$

If the estimation is well calculated, the error term vector is computed based on Eq. 9 that will be used to generate the control chart, which would be time-independent, usually distributed with zero means.

$$\hat{e_t} = (Y_{(i=1,2,\cdots,m)t} - \hat{Y}_{(i=1,2,\cdots,m)t} \quad (9)$$

Indeed, if a shift is present, the process will no longer be represented by the function f and thus the residual term $\hat{e_t}$ would also be affected and shifted. Further, to find the residual used for control chart, this study uses the MAR model, as indicated in Eq. 10.

$$y_t = c + \emptyset(B)y_t + e_t \quad (10)$$

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

where

$y_t = (y_{1,t}, y_{2,t}, \dots, y_{m,t})'$ is (mx1) vector of variable Y

$c = (c_1, c_2, \dots, c_m)'$ is (mx1) vector of constant value

$e_t = (e_{1,t}, e_{2,t}, \dots, e_{m,t})'$ is (mx1) vector residual, with assumption e_t~IIDN $(0, \Omega)$ and $var(e_t e_t)$=Ω.

$\emptyset$ = coefficient of MAR model, matrix (mxm)

$t = 1,2, \dots,$ n

B = *backshift operator*

m = number of variables

p = order of MAR

In this study, the MAR residual control chart, which involves a number of input and output variables and a fitting technique to find the satisfied residual, is empowered by a multilayer perceptron regressor (MLPRegressor) (Alpaydin, 2010) to obtain good fitting result. MLPRegressor can approximate the nonlinear functions of the input for regression by forming higher-order representations of the input features using intermediate hidden layer.

4. EXPERIMENT RESULT AND DISCUSSIONS

4.1 Manufacturing process

This study implements the proposed MAR-ANN model for electronics products. The target manufacturing process of the product includes stamping, electroplating, injection molding, assembling and packaging, as shown in Figure 2. An automatic optic inspection (AOI) system is installed in the process to measure product features. The proposed MAR-ANN model allows the quality defects to be easily detected.

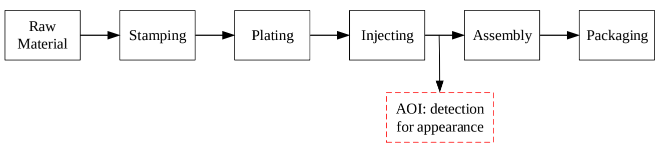


Figure 2. Manufacturing process of the product under investigation

Defect types of "overflowed", "extra-materials" and "metal debris" are key items, which are detected by AOI. The specification measured by AOI system is based on the numerical value, such as length, width, and area. In this study, six features are controlled for each product. Table 1 explains the description of each variable. The products are measured by batches, each containing 100 units of product. This study collects 300 batches as the samples for the MAR-ANN control chart.

Table 1. Product feature and variable notation

Feature	Variable notation
Excess metal material appears at the terminal	Y1_1
The appearance of excess colloids in the hold-down of metal	Y1_2
Excess metal material appears on the plastic body	Y2_1
Excess plastic material appears on the edge of the product	Y2_2
Overflowed on both side	Y3
The root overflowed	Y4

4.2 Residual-based Multivariate control by MAR-ANN model

The proposed MAR-ANN model is implemented according to Figure 1.

4.2.1 Data checking

Basically, MAR model is that each of the time series in the system influence each other, so can predict the series with past values of itself along with other series in the system. Granger's causality test is a method for characterizing dependence relations between time series, which is to test this relationship before building the MAR model. Granger's causality tests the null hypothesis that the coefficients of past values in the regression equation is zero [22]. Table 2 exhibits the Granger's causality test result for all possible combinations of the time series in a given data frame and stores the p-values of each combination in the output matrix. There are some p-value less than 5% significance level, which means the corresponding X series (column) causes the Y series (row) is significance. For example, 0.0000 in (row 1, column 2), it refers to the p-value of Y1_2_x causing Y1_1_y. Whereas, the 0.000 in (row 2, column 1) refers to the p-value of Y1_2_y causing Y1_1_x. Therefore, Table 2 shows the evident that overall variables have correlated to each other. It can be concluded that variable Y1_1 and Y1_2; Y1_1 and Y2_2; Y1_1 and Y3; Y2_1 and Y2_2; Y2_1 and Y4; Y2_2 and Y3 are also correlated.

Table 2. Pearson's correlation test between variables

	Y1_1_x	Y1_2_x	Y2_1_x	Y2_2_x	Y3_x	Y4_x
Y1_1_y	1	**0.000***	**0.003***	0.170	**0.003***	0.071
Y1_2_y	**0.000***	1	**0.000***	0.155	0.813	**0.000***
Y2_1_y	0.145	**0.000***	1	**0.027***	0.101	**0.000***
Y2_2_y	**0.000***	0.2957	0.282	1	**0.000***	**0.027***
Y3_y	**0.031***	0.7830	0.094	**0.000***	1	0.281
Y4_y	0.085	**0.000***	0.381	0.101	0.115	1

Note: *) at 5% significance level

ACF test of each variable is shown in Figure 3, showing that almost all variables have lags over than the red likelihood limit (95%), which means every variable has significant autocorrelation. Vector autoregressive model found that the optimal lag to define order *p* is 16 (*p* = 16). This order was chosen based on the minimum Akaike Information Criterion (AIC) value.

4.2.2 MAR modeling process - constructing residuals control chart using ANN model

Eq. 9 represents an autoregressive process with 6 variables and order *p* = 16.

$$Y_{(i=1,2,\dots,6)t} = f(Y_{1(t-1)},\dots,Y_{1(t-16)},\dots,Y_{6(t-1)},\dots,Y_{6(t-16)}) \quad (9)$$

Estimation of the process using ANN provides $\hat{f}$ which allows to predict $Y_{(i=1,2,\dots,m)t}$ as Eq. 10.

$$\hat{Y}_{(i=1,2,\dots,6)t} = \hat{f}(Y_{1(t-1)},\dots,Y_{1(t-16)},\dots,Y_{6(t-1)},\dots,Y_{6(t-16)}) \quad (10)$$

Using the MLPRegressor which involved multiple outputs, in a sample containing 14,000 observations, the selected optimal model that used in this study is shown as following:

```
Model=MLPRegressor(activation='relu',alpha=0.0001,b
     atch_size='auto',beta_1=0.999,beta_2=0.999,ear
     ly_stopping=False,epsilon=1e08,hidden_layer_si
     zes=(50,),learning_rate='constant',learning_ra
     te_init=0.001,max_fun=15000,max_iter=1000,mome
     ntum=0.9,n_iter_no_change=10,nesterovs_momentu
     m=True,power_t=0.5,random_state=None,shuffle=T
     rue,solver='adam',tol=0.0001,validation_fracti
     on=0.1,verbose=False,warm_start=False)
```

This model provides an R-square equal to 91.4%. Furthermore, based on the MLPRegressor model we calculate the residual of model and then do the residual checking to know whether the residual fulfilled white noise assumption. The residual can be found easily by subtracting the fitted value from the ANN model from each corresponding observation on each *Y*.

Moreover, in terms of white noise checking, residuals should follow multivariate normal distributions with mean of zero and variance equal to one, and the residuals are free of auto-correlation effects. The following step is a checking of white noise assumptions of residuals. Firstly, multivariate normal distribution checking in this study is done by the Henze-Zirkler test [41]. According to this test, we found that the p-value is equal to 0.150, which means all of residual variables have already followed multivariate normal distributions with significance value at 5%.

Next, independence assumption checking for residuals is conducted by ACF, as shown in Figure 3. The lags of residual variables Y1_1; Y1_2; Y3 and Y4 are lower than the red likelihood limit (95%) and the autocorrelation value is around zero. Meanwhile, the lags are over than the red likelihood limit (95%) and the autocorrelation value is lower than 0.4 for residual variables Y2_1 and Y2_2, which means the correlation is weak so the effect can be ignored. Therefore, it can be concluded that all residual variables are free of the autocorrelation effect. Therefore, those residual variables can be used to create multivariate control chart.

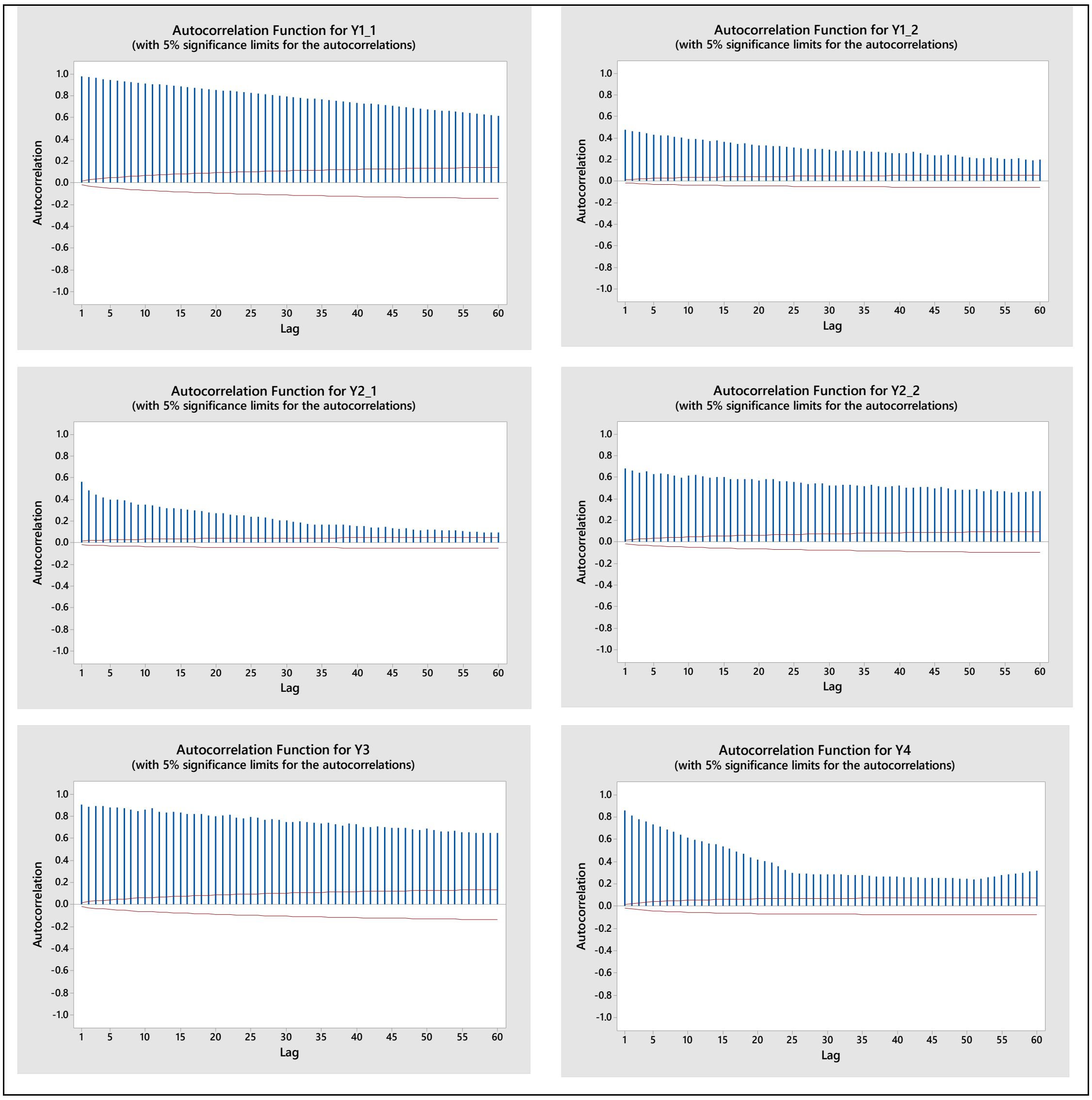


Figure 3. Autocorrelation test of each variable

Third step is residual white noise checking. Table 3 shows that the mean and variance of each residual variable almost near zero. Therefore, all residual variables have already satisfied the white noise assumption. The application of residual data satisfied the assumption of normality distribution and absence of autocorrelation effects.

Table 3. Descriptive of residual model of each variable

Residual of variable	Mean	Variance
Y1_1	-0.001	0.0234
Y1_2	0.081	0.3685
Y2_1	-0.037	0.2193
Y2_2	0.024	0.148
Y3	-0.002	0.0004
Y4	0.052	0.627

All quality characteristics are monitored simultaneously. Table 4 illustrates the correlation among the six residual variables.

Multivariate T^2 Hotelling control chart

Multivariate T^2 Hotelling control chart is constructed. Multivariate T^2 Hotelling control chart for original data with upper control limit (UCL) value equal to 29.2 is illustrates in figure 5(a) showing that there were 50 instances where the mechanism failed, which shown by some points are out of control. There are oscillating and it fails out at points particularly after sample 157th. This behavior comes from the dependence of measurements over the time on original data.
Instead, by using residual data, the number out-of-control samples decreases down to 9 samples. Multivariate T^2 Hotteling control chart using residual data is more stable than multivariate T^2 Hottelling control chart using original data, as shown in Figure 5(b).

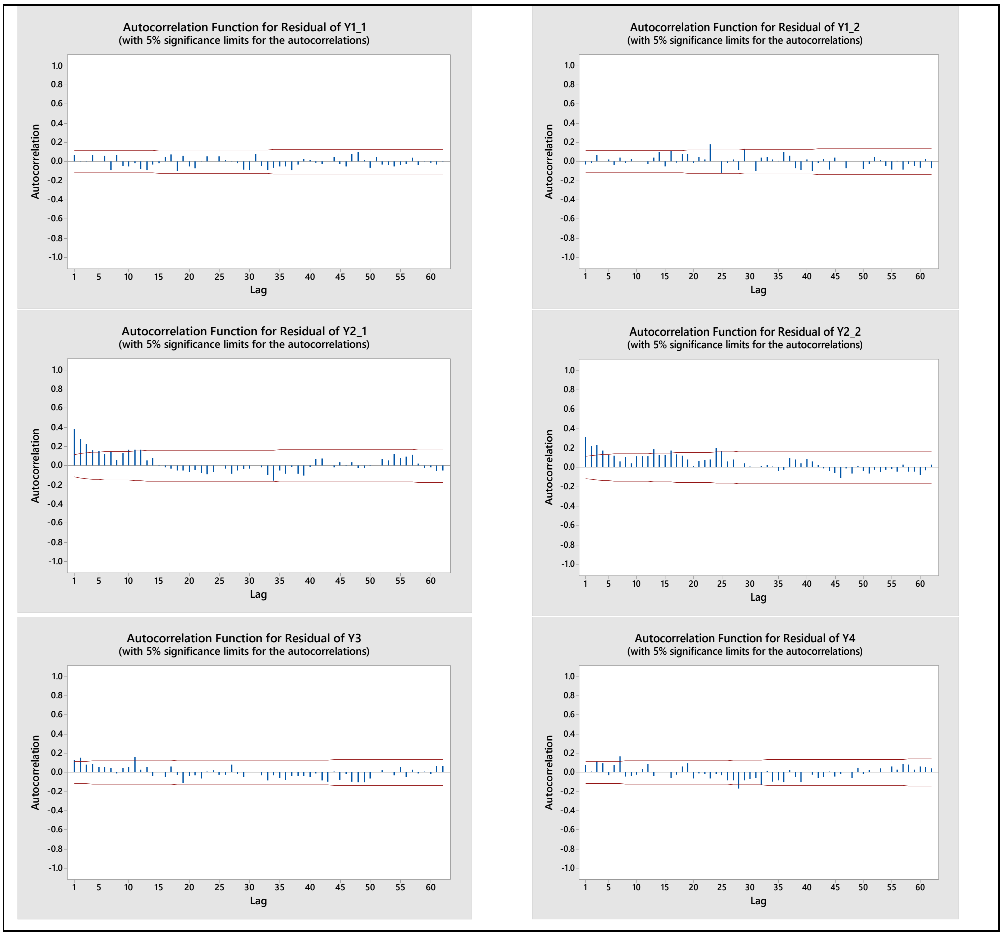
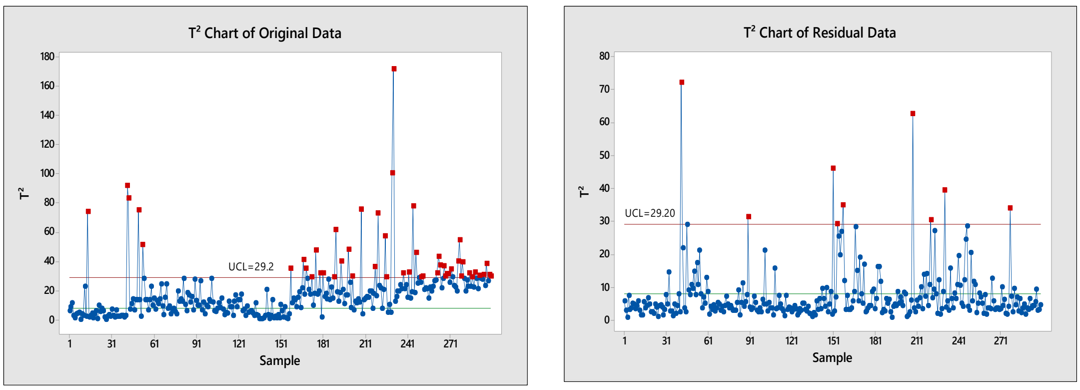


Figure 4. Autocorrelation test of each residual variable

Table 4. Correlation test between residual variables

Characteristics \ Variables		Residual of Y1_1	Residual of Y1_2	Residual of Y2_1	Residual of Y2_2	Residual of Y3
Residual of Y1_2	Correlation	0.046				
	P-Value	0.431				
Residual of Y2_1	Correlation	-0.092	0.064			
	P-Value	0.111	0.266			
Residual of Y2_2	Correlation	0.105	0.112	-0.019		
	P-Value	0.069	0.052	0.743		
Residual of Y3	Correlation	0.189	0.087	0.035	0.064	
	P-Value	**0.001***	0.133	0.542	0.268	
Residual of Y4	Correlation	0.272	0.033	0.131	-0.014	0.144
	P-Value	**0.000***	0.571	**0.023***	0.808	**0.013***

Note: *) at 5% significance level



(a) by original data (b) by residual data

Figure 5. T^2-Hotteling Multivariate control chart

Decomposition is a useful diagnostic technique for out-of-control signals in multivariate control charts. It decomposes the statistic T^2 portion into components that represent each individual variable 's contribution to out-of-control signal. This method is applied by estimating the values of d_i and concentrating on the variables with d_i which are fairly large. Table 5 presents the largest contributor variable that is responsible for the out-of-control signal in multivariate T^2 Hotteling control chart. Y1_2, Y2_1, and Y3 are responsible for out-of-control signals on sample 231st, 154th, and 42nd, respectively. Y1_1 is responsible for samples 90th and 278th. Y2_2 is responsible for samples 208th and 221st. Y4 is responsible for samples 151st and 158th.

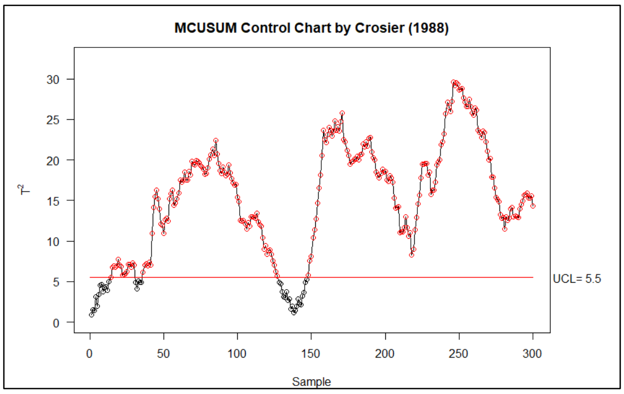
Table 5. Decomposed T^2 Hotteling value

Sample	Variables					
	Y1_1	Y1_2	Y2_1	Y2_2	Y3	Y4
42	11.44	0.922	3.919	0.756	41.316	3.766
90	14.47	0.187	0.007	4.659	0.518	4.742
151	0.033	0.726	0.312	0.115	1.314	39.02
154	10.73	0.390	15.44	2.142	0.145	0.559
158	1.450	0.622	7.821	0.239	0.044	19.47
208	5.918	8.376	0.967	40.04	1.127	1.883
221	0.066	0.101	4.608	26.74	1.552	0.113
231	3.693	24.50	0.721	2.862	7.022	0.302
278	21.09	1.052	0.119	0.005	2.198	3.815

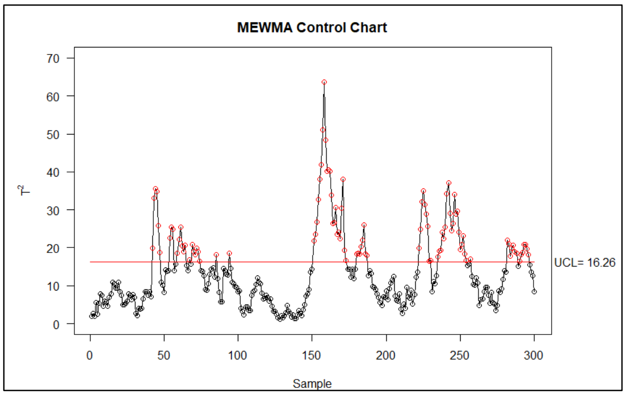
MCUSUM and MEWMA control chart

MCUSUM and MEWMA routines developed in Rstudio (2020) with MSQC packages were applied to generate these charts. We adopted $ARL_0 = 200$, i.e. false alarm rate $\alpha = 0.05$, reference value $k = 0.5$ and the decision limit $h = 5.5$.

The performance of the MCUSUM control chart of residual data in terms of sensitivity can detect small changes in the mean vector of this process as compared with the T^2 Hotteling control charts under the same conditions, i.e. for $p = 6$; $n = 1$ and $ARL_0 = 200$, as shown in Figure 6(a). As the first signal was happened at sample 42nd in the multivariate T^2 Hotteling control chart, the MCUSUM control chart detects the first signal is at sample 14th. On the other hand, Figure 6(b) shows the MEWMA control chart has the same sensitivity with T^2 Hotteling control chart in detecting changes in the process.
Implementing T^2 Hotteling control chart, MCUSUM chart and MEWMA chart for the obtained residual data can overcome multivariate autocorrelated data effectively. When compared with MCUSUM and MEWMA, T^2 Hotteling has better performance in detecting small shifts in the process. Meanwhile, the MCUSUM residual chart and the MEWMA residual chart show a large shift from the average. In addition, T^2 Hotteling also shows stable shifts around the average. However, the MCUSUM chart and the MEWMA chart show oscillations in shifts and even show a trend. This shows that the T^2 Hotteling residual chart has better performance than the MCUSUM and MEWMA residual control charts.



(a) MCUSUM control chart



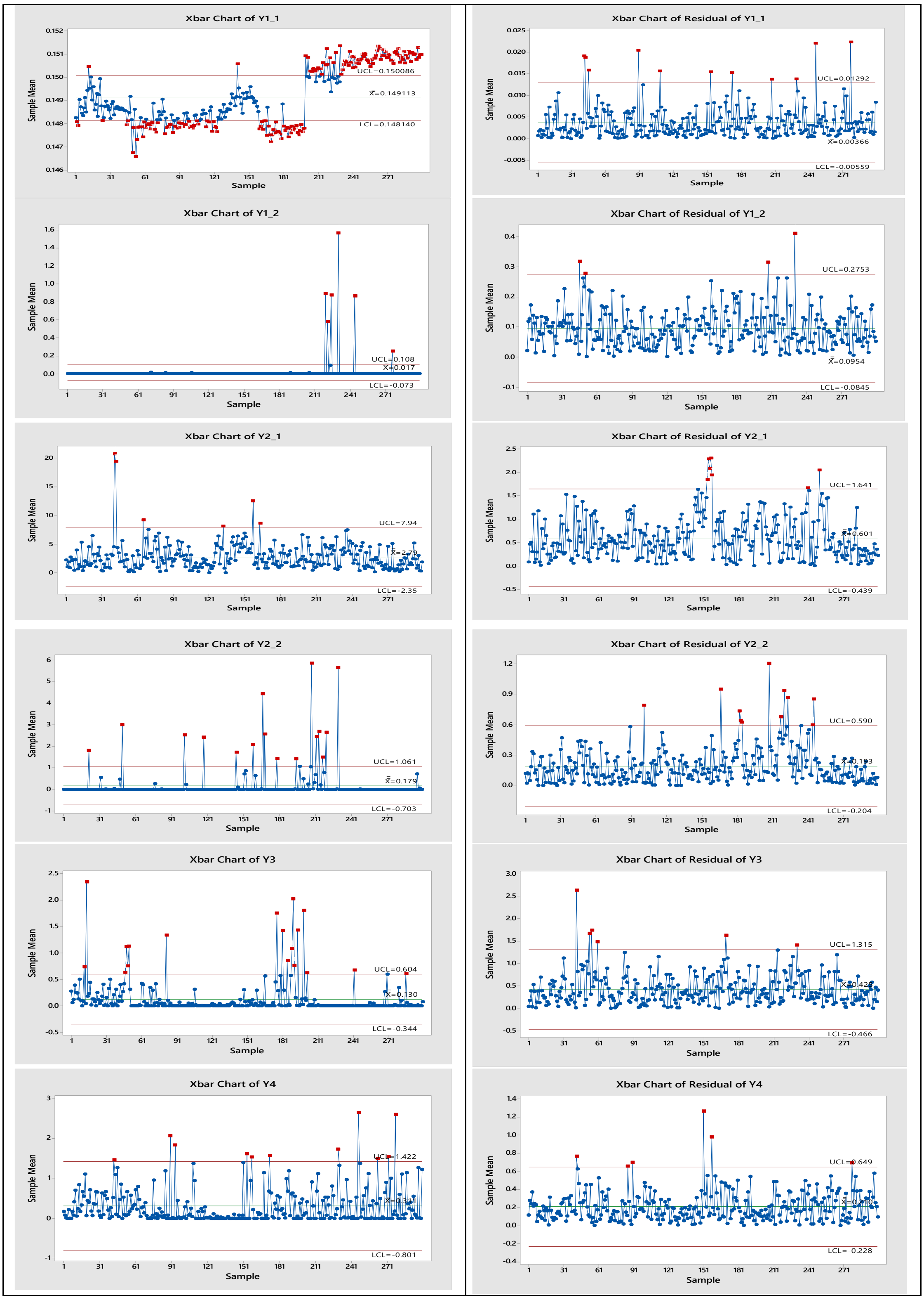
(b) MEWMA control chart

Figure 6. Multivariate control charts using residuals data

4.3. Comparison univariate control chart between original and residual data

In this section, we exhibit the comparison between univariate control chart based on original data and residual data as shown in Figure 7. This comparison shows that residual control chart has better performance than the original data if the original data have time series effect which shown by the high autocorrelation. Figure 7 shows that control charts based on the original data have more out-of-control data than control chart based on residual data. Using three times of standard deviation from the center line rules, based on original data control chart, there are 181 samples, 6 samples, 6 samples, 16 samples, 18 samples, and 11 samples are out-of-control for each variable Y1_1, Y1_2, Y2_1, Y2_2, Y3 and Y4; respectively. Otherwise, using the same rules for testing, based on the residual data control chart, number of samples out of control decreasing into 11 samples, 4 samples, 7 samples, 11 samples, 6 samples and 6 samples for each variable Y1_1, Y1_2, Y2_1, Y2_2, Y3 and Y4; respectively. Even though variable Y2_1 has increasing number of samples out of control in residual data control chat, but there five consecutive points of out-of-control samples are getting large shift from the centerline.

The overall impression of process stability shown by control charts using residual data are rather different than was obtained from the control charts based on the original data. Otherwise, univariate control chart by original data for each variable, the pattern also shows the trend and large shift from the average. It might cause by the autocorrelation effects that happened on original data. As shown by the Figure 3, we see that the autocorrelation effect of the original data is very high which shown by the significant lag.



(a) (b)

Figure 7. Univariate control chart: (a) $\bar{x}$ control chart of original data; (b) $\bar{x}$ control chart of residual data

5. CONCLUSION

The case study examined in this paper reveals that the test of autocorrelation and the analysis of the time series are critical preliminary steps in the application of control charts. The performance of control charts is deteriorated by auto-correlated observations. As observed in charts built using original data, it increases the false alarm rate. It should also be noted that in applying multivariate control charts the existence of auto-correlated observations may mask the actual correlation between variables. Moreover, dependency among the variables also has effect to the performance of univariate control chart. Hence, it is better using multivariate control chart. Therefore, it is recommended to use MAR model using ANN approach to reduce autocorrelation effect on multivariate data.

In order to identify out-of-control signals in multivariate control charts, it is possible to use univariate control charts as it is easy to implement. However, in cases associated with actual correlation among variables, the univariate control charts can result in misleading conclusions. Instead, decomposing statistics is a suitable technique that can be used in T^2 Hotteling multivariate control charts to identify the contribution of variables in out-of-control signals.

Analyzing the results of the considered case study indicates that in situations where it is important to detect small changes in process parameters, the MCUSUM and MEWMA charts are alternatives to the T^2 Hotelling control chart. In such situations, these control charts have better run length performance and more sensitive than the T^2 Hotelling control chart to detect a small change in the process's mean vector, which allows faster action. Since the data that used in this study come from specification product measured by AOI system is based on numerical value, an interesting future research concerns of P control chart, which related to the defect proportion control chart, will be gave analysis and interpretation of control chart with image data as an input data.

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Revisions Required MMEP MM 1

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After careful consideration, we have determined that revisions are necessary before your work can be further considered for publication. Please attend to the following:

[1] **Manuscript Revision:** Incorporate the reviewers' suggestions into your manuscript. Clearly indicate all modifications and include a response letter detailing how each comment was addressed.

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[3] **Figures:** Submit all original figures in editable format, or adjust the text within figures to Times New Roman, 10 point font.

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Auto-correlated Multivariate Quality Control for Electronic Products Manufacturing with Decomposition Analysis

Comments 1

1. The paper is generally well-structured, but some sections require better organization to enhance readability and coherence. For instance, the introduction could more explicitly state the research gaps and how this paper aims to fill them.
2. The abstract provides a good summary of the paper but could include a brief mention of the key findings and implications to strengthen its impact.
3. The literature review is comprehensive; however, it mostly lists previous works without critically analyzing or comparing these methods in detail. A deeper analysis of how the proposed ANN-based model differs or improves upon existing methods would be beneficial.
4. Include more recent studies to ensure that the review is up-to-date, as this field is rapidly evolving.
5. The introduction provides good background but does not sufficiently highlight the specific gaps in the literature or limitations of existing methods that this work aims to address. Please expand the introduction to clearly state the issues with current multivariate autocorrelated process monitoring approaches that this study seeks to overcome.
6. More details are needed on the data collection, manufacturing process, and variables measured. Things like measurement accuracy, instrumentation calibration, data preprocessing, etc. should be discussed to provide context.
7. The proposed MAR-ANN methodology requires more specifics on model selection, optimization, and validation to demonstrate its appropriateness. Details on training, validation, hyperparameter selection, and performance metrics should be added.
8. The description of the ANN model and its configuration (such as architecture, training data, and hyperparameters) is vague. A more detailed explanation is necessary to allow reproducibility and to assess the appropriateness of the chosen techniques.
9. The statistical validation of the model needs to be more robust. Consider adding more metrics for performance evaluation and comparing these with traditional multivariate quality control charts.
10. While the results indicate that the proposed model performs well, the discussion lacks depth in terms of interpreting these results in the context of manufacturing realities. Discuss the practical implications of implementing this model in a real-world setting.
11. The sensitivity analysis of the model to changes in its parameters or variations in data quality could enhance the paper's contribution to the field.
12. It would benefit from greater clarity and cohesion in conclusion. Specifically, it could enhance its effectiveness by clearly quantifying the comparative analysis of different control charts and explicitly linking these findings to the supporting data presented earlier in the paper.
13. The reference format generally meets journal requirements, but some references are outdated. It is recommended to include more recent research findings, all of which should have a DOI or be searchable on Google.

Comments 2

1. The literature review section needs to be strengthened. While it covers key topics like multivariate auto-correlated control charts, residual control charts, and applying ANN to statistical process monitoring (SPM), the synthesis and critical analysis of prior work is lacking. The authors should identify specific gaps in the existing research that their proposed methodology aims to address. This will help position the novelty and significance of their work more clearly.
2. The methodology description requires more details for reproducibility. Equations are provided for the MAR model and residual calculations, but the explanations around them are brief. Elaborate on the ANN architecture (number of layers, nodes, activation functions, etc.) and training process used. Specify hyperparameter settings. The procedure diagram in Figure 1 is helpful, but the steps need to be described in greater depth in the text.
3. The results focus heavily on qualitative interpretations of control chart patterns. Please add more quantitative analysis and numerical comparisons of method performance, such as false alarm rates, out-of-control run lengths, and fault detection rates.
4. Discussion of results should include more interpretation rather than just presentation. What are the key insights and practical implications? How generalizable is the approach to other manufacturing contexts? Acknowledge any limitations of the method and scope for future enhancements.
5. The conclusions are too broad and lacking specifics. Please provide more detailed and quantified conclusions on the performance of the proposed MAR-ANN approach compared to other methods.
6. Writing can be made more concise and clear in some parts, especially the introduction. Avoid redundant phrases. Use paragraphs effectively to separate key ideas. Check grammar, typos and formatting consistency thoroughly before resubmission.

3. Revised version received (09-07-2024)

-Revisions and Amends

-Revised version with highlights

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Auto-correlated Multivariate Quality Control for Electronic Products Manufacturing with Decomposition Analysis

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multivariate statistical process control, decomposition analysis, residual control chart

ABSTRACT

Most modern industrial process outcomes are multivariate, and univariate control charts can lead to misleading conclusions in the case of high correlation among variables. This paper presents a novel multivariate statistical process control method to monitor electronic products with multivariate correlated outcomes. We develop a procedure for monitoring multivariate autocorrelated data using a multivariate autoregressive (MAR) model with neural networks. This study investigates the significance and sensitivity of using MCUSUM, MEWMA, and T^2 Hotelling charts to detect small changes in the mean vector of a process. The identification of out-of-control signals generated from multivariate statistical process control is derived from univariate charts and a decomposition approach. Our proposed decomposing statistics determine the contribution of variables in out-of-control signals by T^2 Hotelling multivariate control charts. Additionally, MCUSUM and MEWMA control charts demonstrate good run length performance and high sensitivity in detecting small changes in the process's mean vector, enabling prompt corrective actions. These findings suggest that the proposed method enhances the reliability and responsiveness of quality control in electronic product manufacturing.

1. INTRODUCTION

The complexity and increasing correlation of product features over time have made the requirements of product inspection more difficult. Statistical process monitoring is a method of quality control since variability is a primary indication of poor quality [1]. In many continuous processes of the electronic device manufacturing business, statistical process monitoring (SPM) typically develops over time to handle auto-correlated, multivariate quality data. Any changes in a process that may be the consequence of unforeseen and uncontrollable factors can be quickly identified by an effective SPM system.

Traditional control charts relied on the idea that the process would be dispersed independently across time, but as electronic device manufacture has advanced, this assumption is no longer valid. Control charts are produced for variables that defy one of the primary assumptions, serial-sample independence, when autocorrelation is present. The Average Run Length (ARL) and stability of the control charts are both impacted by the violating of the presumption of independence [2]. Furthermore, if there are too many false alarms, the process engineer may prefer to completely ignore the control charts or misidentify the true source of variation. This explains why control charts are used on continuous-flow systems very infrequently [3].

Due to the fact that the industry that manufactures electrical products typically bases its product quality on a number of interconnected quality criteria and variables, SPM is also faced with multivariate problems [4]. The statistical characteristics of classic control charts are greatly impacted by interrelated variables, which can also result in a notable rise in the average false alarm rate and a fall in the capacity to identify process changes. Applying univariate control charts to every variable has the potential to mislead in decisions about quality. Consequently, multivariate based quality control techniques needed to take such characteristics into account at the same time.

The requirements of product inspection have become more challenging as product attributes become complex and increasingly correlated over time. Statistical process monitoring (SPM) is a crucial tool in quality control, but traditional SPM systems face significant challenges in modern electronic product manufacturing. One major issue is that traditional control charts assume data is independently distributed, which is often violated due to autocorrelation, leading to instability, and increased false alarms. Additionally, traditional control charts are not designed to handle multiple interrelated quality attributes simultaneously, which can mislead quality decisions and reduce the ability to detect process changes. These challenges have resulted in a low adoption of control charts in continuous-flow systems. This paper aims to address these gaps by proposing advanced SPM techniques that account for autocorrelation and introducing multivariate-based quality control methods to handle interrelated attributes simultaneously. Through these enhancements, we seek to increase the reliability and practical utility of control charts, encouraging their broader adoption in the electronic product manufacturing industry.

Traditional SPM methods, such as Shewhart, CUSUM, and EWMA control charts, assume that process data is independently distributed over time. However, this assumption is often violated in modern manufacturing environments where autocorrelation is prevalent. The violation of the independence assumption leads to several issues with traditional control charts: increased false alarms, decreased sensitivity, and complexity in handling multivariate data. Existing multivariate control charts, such as T^2 Hotelling's, MCUSUM, and MEWMA, address these correlations but are often complex to implement and may not effectively decompose out-of-control signals to identify specific variable contributions.

To address these limitations, our study proposes a novel ANN-based multivariate statistical process control model that integrates a multivariate autoregressive (MAR) approach with neural networks. This model aims to enhance detection sensitivity, improve robustness to autocorrelation, and provide detailed decomposition of out-of-control signals. By leveraging the capabilities of neural networks, our model improves sensitivity to small shifts in the process mean vector, ensuring timely detection of quality issues. The integration of MAR with neural networks effectively manages autocorrelated data, reducing false alarms and improving the stability of Average Run Length (ARL). Additionally, our model offers a detailed decomposition of out-of-control signals, using univariate charts and a decomposition approach to identify specific variable contributions. This feature allows process engineers to pinpoint and address root causes of variations more accurately. By addressing these specific gaps and limitations in current multivariate autocorrelated process monitoring approaches, our study aims to enhance the reliability and practicality of SPM systems in modern manufacturing environments, ultimately improving product quality and manufacturing efficiency.

The present study will address the auto-correlated, multivariate quality control for electronic product manufacturing. We propose a model based on ANN to predict and build the residual based control chart for multivariate data with autocorrelation order *p* (AR(*p*)) processes.

The rest of this paper is organized as following. Section 2 discusses relevant literature review, such as SPM of multivariate auto-correlated observations, multivariate control chart, and ANN for multivariate and auto-correlated observations. Section 3 details the research methodology including manufacturing process and research variables. Section 4 illustrates a practical application and discussion. Finally, conclusions are provided in Section 5.

2. LITERATURE REVIEW

2.1. Multivariate auto-correlated control charts

Autocorrelation is common in both continuous and batch operation processes, prompting ongoing research for solutions [5]. Loredo introduced regression adjustment-based monitoring for autocorrelated processes[6]. Psarakis and Papaleonida [7] noted that even low levels of autocorrelation can significantly affect traditional control charts, raising false alarm rates and reducing detection ability. A solution is to filter out autocorrelation using a time series model and apply control to the uncorrelated residuals, enabling the use of standard control charts. Callao and Rius [8] showed that residual control charts, especially with an AR(1) model, effectively track device behavior over time and improve detection. Extending univariate methods, multivariate systems can also be monitored and controlled. Khediri and Mohamed [9] proposed using multivariate autoregressive (MAR) models for systems with serial correlations among multiple variables, introducing an MAR control chart for these multivariate autocorrelated processes. Their research proposed an MAR control chart for multivariate auto-correlated processes. For an MAR process with *m* variables, it is denoted by $\mathbf{x_t} = \left(\mathbf{x_{1t}}, \mathbf{x_{2t}}, \ldots, \mathbf{x_{mt}}\right)$ as a $(m \times 1)$ vector.

Psarakis and Papaleonida [7] explained that shifts in the mean or variance of residuals signal changes in the actual process's mean or variance. By plotting residuals on a control chart, shifts in the process can be detected. The principle of residual charts is that, with a correct time series model, residuals become independently and identically distributed random variables, satisfying traditional quality control criteria and enabling the use of standard SPC charts. Therefore, developing an accurate time series model for multivariate autocorrelated data is essential in statistical process control. Although the ARIMA model is widely used for linear time series prediction, it struggles to capture nonlinear patterns.

To resolve the autocorrelation issue, researchers seek for solutions. Alwan and Roberts [10] introduced an approach to deal with autocorrelation in creating of control chart by using residual based control chart. Woodall and Faltin [11] examined how self-correlation affects the results of control charts and proposed strategies for managing autocorrelation. They explored various approaches to address autocorrelation issues, including the development of methods like the cumulative sum (CUSUM) control chart tailored for autocorrelated data [12], [13], [14]. Further, researchers [15], [16], [17], and [18] also developed control charts with autocorrelation data by exponentially weighted moving average (EWMA) control chart.

The literature discusses various multivariable control charts, including the T^2 Hotteling, multivariate cumulative sum (MCUSUM), and multivariate exponentially weighted moving average (MEWMA) control charts [19], [20], [21], and [22]. Researchers have also enhanced control charts to handle multivariate autocorrelated data with time series effects [23], [24], [25], [26], and [27]. Jarrett and Pan [28] developed multivariate control charts for independent processes and univariate control charts for autocorrelated processes. They proposed a multivariate autoregressive (MAR) control chart specifically for multivariate autocorrelated processes.

2.2. Residual control chart

2.2.1. T^2 Hotelling Control Chart

The T^2 Hotelling control chart, a multivariate extension of the Shewhart-type control chart, was introduced by Harold Hotelling in 1947 to handle multivariate observations. There are two versions: one for subgroup data and one for individual observations. The Shewhart *X*-chart is a simple univariate statistic for measuring process stability against significant shifts. Residuals are assumed to have a mean of zero and a standard deviation of σ_r, and an observation is considered in control if the residual value r_i falls within control limits defined by λ. This chart uses the Mahalanobis distance [25] to reduce residuals to a single scalar value. An observation is considered in control if it satisfies the following Eq. 1:

$$T_i^2 = R_i^T \sum_R^{-1} R_i \frac{m(n-1)}{n-m} F_{m;n-m;(\alpha)};\ \text{for } i = 1,2,\cdots,n \quad (1)$$

where *n* is the number of observations, *m* is the number of variables, R_i is the residual vector, $F_{m;n-m;(\alpha)}$ is the Fisher distribution, and $\sum_R^{-1} R_i$ is the inverse of the estimated residual covariance matrix. The term α represents the risk level, ensuring a desired in-control Average Run Length (ARL) or in-control false alarm rate.

2.2.2. Multivariate CUSUM control chart

The CUSUM chart was created to address the limitations of Shewhart and T^2 Hotelling control charts, which are often insensitive to moderate changes since they only use the most recent observation data [9]. In contrast, CUSUM charts are designed to detect subtle process changes by accumulating deviations from a specified target across residuals from previous observations. The most widely used CUSUM control method is Crosier's chart. For $S_0 = 0$, where 0 represents a matrix of zeros of size 1× *m*, the statistical procedure is as follows:

$$S_i = \begin{cases} 0 & \text{, if } C_i \le k \\ (S_{i-1} + R_i)\left(1 - \frac{k}{C_i}\right) & \text{, otherwise} \end{cases} \quad (2)$$

$$C_i = (S_{i-1} + R_i)\Sigma_R^{-1}(S_{i-1} + R_i)^T \quad (3)$$

Crosier's chart signal a shift when $T_S^2 = S_i^T \sum_R^{-1} S_i$ overcomes a predetermined limit *H*. The CUSUM scheme signals a process change when the S statistics exceed a predefined threshold *H*. Thus, if $S_i > H$, the chart indicates a process shift. To achieve the desired in-control run length (RL) characteristic, the parameters *k* and *H* must be determined beforehand. In CUSUM procedures, it is standard practice to assume a sample size of one. This simplification is widely adopted as it allows for the continuous monitoring of individual observations, facilitating the prompt detection of small shifts in the process. However, in some cases, it might be beneficial to consider larger sample sizes to account for variations and provide more robust detection capabilities, especially in processes where data is naturally grouped or collected in batches. Adapting the CUSUM procedure to accommodate different sample sizes can enhance its flexibility and effectiveness in various industrial and statistical applications. The Multivariate CUSUM (MCUSUM) statistic S_i is designed to detect specific shifts in the process mean vector. This capability enables the identification of changes across multiple variables simultaneously, making MCUSUM particularly useful for monitoring complex processes where interactions between variables may signal deviations from the expected process behavior. By accumulating deviations from the target mean vector over time, the MCUSUM statistic provides a sensitive measure for detecting even small shifts, thus enhancing the ability to maintain quality control and process stability in multivariate settings. Additionally, the MCUSUM approach can be tailored to different types of shifts and can incorporate various weighting schemes to prioritize certain variables or shifts, further improving its applicability and effectiveness in diverse industrial and research environments:

$$S_i = max\{S_{i-1} + a^T R_i - k, 0\} \quad (4)$$

where,

$$a^T = \frac{\delta_r^T \Sigma_r^{-1}}{\sqrt{\delta_r^T \Sigma_r^{-1} \delta_r}}$$

δ_r represents the residual mean vector, and Σ_r denotes the variance-covariance matrix. In an MCUSUM scheme, deviations exceeding k units from the target mean are accumulated. Here, *k* acts as the benchmark value for the scheme. The control scheme indicates an out-of-control state when the value of S_i surpasses a predefined decision threshold, denoted as *H*.

2.2.3. Multivariate EWMA control chart

While CUSUM charts consider all past measurements equally, EWMA (Exponentially Weighted Moving Average) charts assign weights to recent observations based on their significance in depicting process behavior. A higher value of λ amplifies the impact of the most recent observation [5]. The iterative expression for EWMA statistics is described by Equation 5,

$$Z_i = (1 - \lambda)Z_{i-1} + \lambda R_i\ ;\ \text{for } i = 1,2,\cdots,n \quad (5)$$

where λ is diagonal matrix of value $0 \le \lambda_j \le 1$, $j = 1,2,\cdots,m$. The multivariate EWMA (MEWMA) scheme signals if the

$$T_Z^2 = Z_i^T \sum\nolimits_Z^{-1} Z_i \quad (6)$$

surpasses a predetermined value *H*, where H > 0 is chosen to achieve a specified in-control (on-target) ARL_0. The asymptotic form of the covariance matrix is $\Sigma_Z = \left(\frac{\lambda}{2-\lambda}\right)\Sigma_R$ [30].

Reynolds and Lu [31] investigated AR(1), AR(2) and ARMA(1,1) models for a residual X-chart and pointed out that the residual X-chart may lack the capacity to detect the mean shift of the processes. Those research, however, considered only for processes which has small order of *p* on autoregressive AR(*p*) model. Whereas real condition sometimes autocorrelation with high order (*p* > 5) are occurred. Besides that, multivariable with high autocorrelation also must considered in one time. This condition usually occurs in the manufacturing industry with mass production and fast flow production. Therefore, the general multivariate autoregressive (MAR) models should be developed to overcome multivariable and autocorrelation problem on statistical process monitoring using residual based multivariate control chart.

2.3. Applying ANN to SPM of multivariate auto-correlated observations

Artificial neural network (ANN) is an estimation tool for the output process (responses) [32]. Multi-layer perceptron (MLP) is a nonparametric estimator that can be used for classification and regression. A multilayer feed forward ANN with continuous output layer is suitable for regression problem.

If an AR(p) model exhibits autocorrelated behavior in quality characteristics, the mean vector for each period depends on the mean vectors of the previous p periods. Consequently, when using an Artificial Neural Network (ANN) for forecasting, the inputs consist of quality characteristic vectors from the previous p periods, and the output is the forecasted quality characteristic vector for the desired time. During implementation, to generate the forecasted vector at the output layer, the network incorporates the characteristics from the preceding p periods into the input layers. According to Arkat et al. [3], the vector of residuals for each period represents the difference between the forecasted and actual values of the quality characteristic vectors.

Over the last two decades, research in statistical process monitoring fields and practices applied machine learning to detect and diagnose faults of the industrial operation process and production results**.** In terms of data analysis in SPM, artificial neural network (ANN) has been applied since 1980s [3]. Some scholars studied ANN applications in univariate control chart, such as [33], [34], and [35]. ANN has also been applied to monitor multivariate processes, such as [36], [37], [38], [39], and [40]. Arkat et al [3] designed an ANN-based model to forecast and construct residual CUSUM chart for multivariate autoregressive of order one, AR(1), processes. Khediri et al. [5] proposed support vector regression to construct several control charts that allows monitoring of multivariate nonlinear auto-correlated processes.

2.4. Summary

Traditional methods often assume independence between observations, which is violated in continuous-flow manufacturing processes due to autocorrelation. This violation leads to increased false alarm rates and reduced average run length (ARL). While multivariate control charts address correlation among variables, they can be complex and computationally intensive, and they may not effectively identify specific variable contributions in out-of-control signals. Our proposed ANN-based model addresses these limitations by integrating a multivariate autoregressive (MAR) approach with neural networks, improving sensitivity to small shifts in the process mean vector and enhancing robustness to autocorrelation. The model offers better detection capabilities, reducing false alarms and improving ARL stability. Additionally, it provides detailed decomposition of out-of-control signals, allowing process engineers to pinpoint and address root causes of variations more effectively. These improvements enhance the reliability and practicality of SPM systems in modern manufacturing, leading to more timely and accurate quality control interventions, ultimately improving product quality and manufacturing efficiency.

In recent years, several studies have advanced the field of SPM, particularly in addressing the limitations of traditional control charts in handling autocorrelated and multivariate data. For instance, Wang and Asrini [29] proposed an enhanced EWMA control chart that incorporates machine learning techniques to better handle autocorrelated data, demonstrating improved sensitivity and reduced false alarm rates. Similarly, Yang and Sutrino [30] developed a hybrid SPM model that combines neural networks with traditional statistical methods to monitor complex manufacturing processes, showing significant improvements in detection capabilities and robustness to data variability.

There is a recurrent violation of independently distribution assumptions with the advance made in many automation processes such as electronic component manufacturing because the high selection of samples creates a set of observations that are close enough to be dependent. How to apply and evaluate control charts designed to account for autocorrelation is critical. Residual control charts provide a good understanding of the device behavior over time and efficient detection capabilities but does not fully fulfill the requirement of autocorrelation and multiple variates observations.

3. METHOD

This study aims to present a residual control chart using MAR model with ANN (MAR-ANN) to solve the SPM problem related to multivariate with auto-correlated observations. Moreover, this study makes diagnostic of out-of-control signal in multivariate control chart using decomposition technique. Comparison of multivariate control chart with univariate one is also conducted. Figure 1 shows the operational procedure of the proposed mothed. Multiple variables are defined as the quality parameter which correlate to each other, and each variable is of time series.

Correlation test is employed to know the strength of correlation between variables. In this study, correlation test determines the correlation between quality parameters of a product. If there is a correlation between quality parameters, then the control chart preparation is based on a multivariate control chart approach because it will involve more than one quality parameter in one chart. The hypothesis used in testing the correlation between quality parameters is as follows. To determine whether there is a correlation between quality parameters is based on the p-value.

H_0: $\rho = 0$ or there is no correlation

H_1: $\rho \neq 0$ or there is a correlation

In terms of autocorrelation, this study applies a method proposed by Loredo [6] for monitoring auto-correlated processes that showed the superiority of residual-based control charts in comparison with observation-based control charts when detecting the mean shift in short-run auto-correlated data processes. Each variable is examined by autocorrelation test to know whether each variable correlates with time changes. The autocorrelation test of each variable can be seen visually through the autocorrelation function (ACF) plot graph. Variables have a significant autocorrelation if there is a significant lag in the ACF plot. To overcome autocorrelation, time series modeling must be done, the model obtained calculates the model error to meet the assumption of white noise. The coefficient of autocorrelation lag k measures the correlation between values of each variable at time t and time t-k and shows the limit of probability around 0. If the autocorrelation graph is below the 95% likelihood limits at a certain lag, a large autocorrelation occurs at that lag.

Figure 1 presents a four-step procedure. First, data are checked for each variable by ACF and correlation between variables by Pearson's correlation. Second, MAR modelling process determines the model considering autocorrelation and multivariate. To estimate MAR, this research proposes an ANN with MLPRegressor approach. Third, residual white-noise checking is conducted to ensure all residual variables can be used for the multivariate control chart. White noise residual checking involves multivariate normality, independence and identical test. Then, fourth step builds a residual-based multivariate control chart where residual is the difference between actual value and estimated value based on the MAR model of each variable.

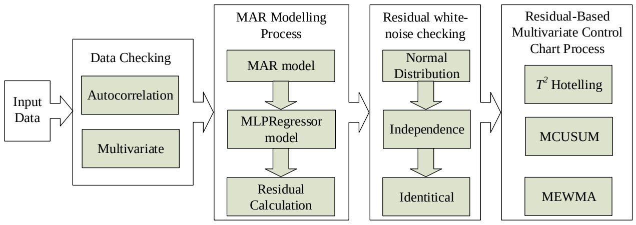


Figure 1. Procedure to build the proposed control chart

If the quality characteristics of an autocorrelated process conform to an AR(p) model, the mean vector for each period depends on the mean vectors of the preceding p periods. In such cases, the inputs for the desired Artificial Neural Network (ANN) consist of the quality characteristic vectors from the previous p periods, while the output represents the quality characteristic vector to be forecasted for the next period. Before constructing the ANN, the Multivariate Autoregressive (MAR) model is typically applied to determine the autoregressive order p for each factor in the time series. This helps in understanding the dependencies and lagged effects among the quality characteristics over time, ensuring that the ANN model captures the relevant temporal relationships effectively.

Based on Khediri et al. [5], this study performs time series estimation for a multivariate process by MAR. Each input variable $Y_{(i=1,2,\ldots,m)t}$ is defined by the previous variables of the series $(Y_{1(t-1)},\ldots,Y_{1(t-p)},\ldots,Y_{m(t-1)},\ldots,Y_{m(t-p)})$, where m is the number of variables and p is the lagged time. Supposed that we have an autoregressive process with m variables and order p that need to be estimated, one can present $Y_{(i=1,2,\ldots,m)t}$ by Eq. 7:

$$Y_{(i=1,2,\ldots,m)t} = f(Y_{1(t-1)},\ldots,Y_{1(t-p)},\ldots,Y_{m(t-1)},\ldots,Y_{m(t-p)}) \quad (7)$$

Estimation of the process using MAR model provides $\hat{f}$ which allows to predict $Y_{(i=1,2,\ldots,m)t}$ as Eq. 8:

$$\hat{Y}_{(i=1,2,\ldots,m)t} = \hat{f}(Y_{1(t-1)},\ldots,Y_{1(t-p)},\ldots,Y_{m(t-1)},\ldots,Y_{m(t-p)}) \quad (8)$$

If the estimation is well calculated, the error term vector is computed based on Eq. 9 that will be used to generate the control chart, which would be time-independent, usually distributed with zero means.

$$\hat{e_t} = (Y_{(i=1,2,\cdots,m)t} - \hat{Y}_{(i=1,2,\cdots,m)t} \quad (9)$$

If a shift occurs in the process, it will no longer be accurately described by the function *f*, and consequently, the estimated residual term $\hat{e_t}$ will also be affected and shifted. To determine the residual used for the control chart, this study employs the Multivariate Autoregressive (MAR) model, as specified in Eq. 10.

$$y_t = c + \emptyset(B)y_t + e_t \quad (10)$$
$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + e_t$$

where

$y_t = (y_{1,t}, y_{2,t}, \ldots, y_{m,t})'$ is (mx1) vector of variable Y
$c = (c_1, c_2, \ldots, c_m)'$ is (mx1) vector of constant value
$e_t = (e_{1,t}, e_{2,t}, \ldots, e_{m,t})'$ is (mx1) vector residual, with assumption $e_t \sim$IIDN $(0, \Omega)$ and $var(e_t e_t)$=Ω.
$\emptyset$ = coefficient of MAR model, matrix (mxm)
$t = 1,2, \ldots,$ n
B = *backshift operator*
m = number of variables
p = order of MAR

In this study, the MAR residual control chart, which involves a number of input and output variables and a fitting technique to find the satisfied residual, is empowered by a multilayer perceptron regressor (MLPRegressor) (Alpaydin, 2010) to obtain good fitting result. MLPRegressor can approximate the nonlinear functions of the input for regression by forming higher-order representations of the input features using intermediate hidden layer.

4. EXPERIMENT RESULT AND DISCUSSIONS

4.1 Manufacturing process

This study applies the MAR-ANN model to electronics product manufacturing processes, encompassing stages like stamping, electroplating, injection molding, assembly, and packaging (depicted in Figure 2). These processes operate on a high-speed continuous production line characterized by multivariate and autocorrelated properties. An Automatic Optical Inspection (AOI) system is integral to the process, facilitating data collection. High-precision instruments, regularly calibrated for accuracy, including digital calipers, micrometers, and AOI systems, are utilized to measure product dimensions and features. Specifically, AOI systems record product feature measurements. The MAR-ANN model proposed in this study aims to enhance defect detection capabilities, leveraging the structured data from AOI and other instruments to improve quality monitoring throughout the manufacturing stages.

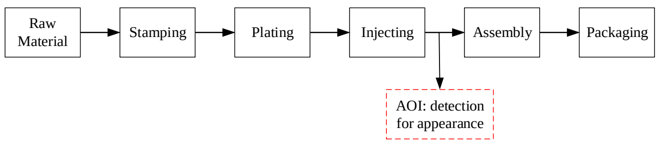


Figure 2. Manufacturing process of the product under investigation

In this study, the Automatic Optical Inspection (AOI) system detects key defect types such as "overflowed", "extra-materials", and "metal debris". These defects are identified based on numerical specifications such as length, width, and area measured by the AOI system. Each product is characterized by six features, as detailed in Table 1, which describes each variable. The data collection process involves measuring products in batches, with each batch comprising 100 units. For the MAR-ANN control chart analysis, this study collects samples from 300 such batches. This structured approach ensures that a comprehensive dataset is used to develop and validate the MAR-ANN model for effective quality control in the manufacturing process.

Table 1. Product feature and variable notation

Feature	Variable notation
Excess metal material appears at the terminal	Y1_1
The appearance of excess colloids in the hold-down of metal	Y1_2
Excess metal material appears on the plastic body	Y2_1
Excess plastic material appears on the edge of the product	Y2_2
Overflowed on both side	Y3
The root overflowed	Y4

4.2 Residual-based Multivariate control by MAR-ANN model

The proposed MAR-ANN model is implemented according to Figure 1.

4.2.1 Data checking

The MAR (Multivariate Autoregressive) model assumes that each time series in the system influences others, allowing predictions based on past values of all series involved. Granger's causality test is a method used to assess these dependency relationships by testing whether past values of one series help predict another. In your study, Table 2 presents the results of Granger's causality test for all possible combinations of time series in a given dataset, storing the corresponding p-values in an output matrix. A p-value less than the 5% significance level indicates a significant causal relationship, where the series in the column influences the series in the row. For example, a p-value of 0.0000 in (row 1, column 2) suggests that Y1_2 (column) causes Y1_1 (row). Conversely, a p-value of 0.000 in (row 2, column 1) indicates that Y1_2 (row) causes Y1_1 (column). Therefore, Table 2 demonstrates that there are significant correlations among the variables overall. Specifically, it can be concluded that variables Y1_1 and Y1_2; Y1_1 and Y2_2; Y1_1 and Y3; Y2_1 and Y2_2; Y2_1 and Y4; Y2_2 and Y3 are correlated based on the p-values obtained from Granger's causality test. These findings help validate the interconnectedness assumed by the MAR model in your analysis.

Table 2. Pearson's correlation test between variables

	Y1_1_x	Y1_2_x	Y2_1_x	Y2_2_x	Y3_x	Y4_x
Y1_1_y	1	**0.000***	**0.003***	0.170	**0.003***	0.071
Y1_2_y	**0.000***	1	**0.000***	0.155	0.813	**0.000***
Y2_1_y	0.145	**0.000***	1	**0.027***	0.101	**0.000***
Y2_2_y	**0.000***	0.2957	0.282	1	**0.000***	**0.027***
Y3_y	**0.031***	0.7830	0.094	**0.000***	1	0.281
Y4_y	0.085	**0.000***	0.381	0.101	0.115	1

Note: *) at 5% significance level

ACF test of each variable is shown in Figure 3, showing that almost all variables have lags over than the red likelihood limit (95%), which means every variable has significant autocorrelation. Vector autoregressive model found that the optimal lag to define order p is 16 (p = 16). This order was chosen based on the minimum Akaike Information Criterion (AIC) value.

4.2.2 MAR modeling process - constructing residuals control chart using ANN model

The proposed methodology integrates a Multivariate Autoregressive (MAR) model with an Artificial Neural Network (ANN) to handle the complexities of autocorrelated and multivariate quality data. The MAR model captures the time-series characteristics and dependencies among variables, while the ANN addresses the nonlinear relationships and enhances the sensitivity to small shifts in the process mean vector. The MAR-ANN model was trained using a dataset collected from a continuous-flow electronic product manufacturing process. The dataset was split into training (70%), validation (15%), and test (15%) sets to ensure the robustness of the model. The training set was used to fit the model, the validation set was used to fine-tune hyperparameters, and the test set was used to evaluate the model's performance. Hyperparameter selection is critical for optimizing the performance of the ANN. We used a grid search approach to determine the optimal hyperparameters, including the number of hidden layers, the number of neurons per layer, learning rate, and regularization parameters. The grid search was performed using cross-validation on the training set, and the combination of hyperparameters that yielded the best performance on the validation set was selected for the final model.

Eq. 9 represents an autoregressive process with 6 variables and order p = 16.

$$Y_{(i=1,2,\dots,6)t} = f\left(Y_{1(t-1)},\dots,Y_{1(t-16)},\dots,Y_{6(t-1)},\dots,Y_{6(t-16)}\right) \tag{9}$$

Estimation of the process using ANN provides $\hat{f}$ which allows to predict $Y_{(i=1,2,\dots,m)t}$ as Eq. 10.

$$\hat{Y}_{(i=1,2,\dots,6)t} = \hat{f}\left(Y_{1(t-1)},\dots,Y_{1(t-16)},\dots,Y_{6(t-1)},\dots,Y_{6(t-16)}\right) \tag{10}$$

The specific ANN model that used to figure out the autoregressive model with 6 variables and order p = 16 in this case is MLPRegressor. The model, trained on 14,000 observations from an electronic product manufacturing process, includes a single hidden layer with 50 neurons and uses the 'relu' activation function. Key hyperparameters include an alpha of 0.0001 for regularization, a learning rate of 0.001, and the Adam optimizer. The model underwent up to 1000 iterations, with early stopping disabled, and employed cross-validation (70% training, 15% validation, 15% test split). These details ensure the model's reproducibility and highlight the robustness and appropriateness of our approach. Using the MLPRegressor which involved multiple outputs, the selected optimal model that used in this study is shown as following:

```
Model=MLPRegressor(activation='relu',alpha=0.0001,batch_size='auto',beta_1=0.999,beta_2=0.999,early_stopping=False,epsilon=1e08,hidden_layer_sizes=(50,),learning_rate='constant',learning_rate_init=0.001,max_fun=15000,max_iter=1000,momentum=0.9,n_iter_no_change=10,nesterovs_momentum=True,power_t=0.5,random_state=None,shuffle=True,solver='adam',tol=0.0001,validation_fraction=0.1,verbose=False,warm_start=False)
```

The R-square value of 91.4% indicates that the MLPRegressor model explains a substantial portion, 91.4%, of the variance in the data, highlighting a strong fit for the MAR-ANN model to the observed values. To verify the white noise assumption of the residuals, the residuals are computed by subtracting the predicted values from the actual observations for each Y variable. Subsequent checks include ensuring the residuals have a mean close to zero, exhibit no significant autocorrelation through plots or tests like the Durbin-Watson test, and demonstrate constant variance (homoscedasticity) across different values. Meeting these criteria indicates that any remaining patterns in the data are likely due to random noise, validating the accuracy and reliability of the model's predictions.

Moreover, in terms of white noise checking, residuals should follow multivariate normal distributions with mean of zero and variance equal to one, and the residuals are free of auto-correlation effects. The following step is a checking of white noise assumptions of residuals. Firstly, multivariate normal distribution checking in this study is done by the Henze-Zirkler test [41]. According to this test, we found that the p-value is equal to 0.150, which means all of residual variables have already followed multivariate normal distributions with significance value at 5%.

Next, independence assumption checking for residuals is conducted by ACF, as shown in Figure 3. The lags of residual variables Y1_1; Y1_2; Y3 and Y4 are lower than the red likelihood limit (95%) and the autocorrelation value is around zero. Meanwhile, the lags are over than the red likelihood limit (95%) and the autocorrelation value is lower than 0.4 for residual variables Y2_1 and Y2_2, which means the correlation is weak so the effect can be ignored. Therefore, it can be concluded that all residual variables are free of the autocorrelation effect. Therefore, those residual variables can be used to create multivariate control chart.

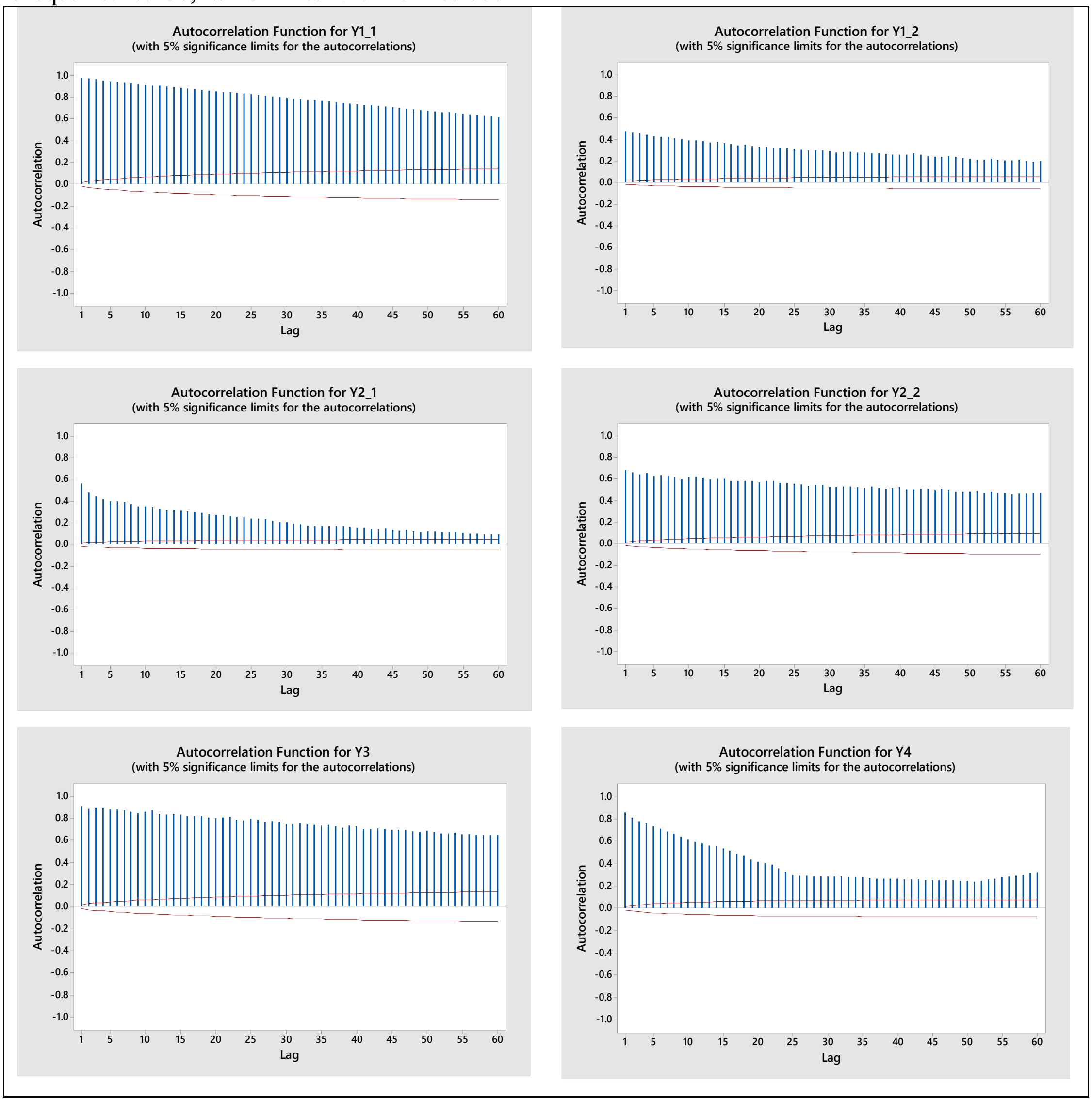


Figure 3. Autocorrelation test of each variable

Third step is residual white noise checking. Table 3 shows that the mean and variance of each residual variable almost near zero. Therefore, all residual variables have already satisfied the white noise assumption. The application of residual data satisfied the assumption of normality distribution and absence of autocorrelation effects.

Table 3. Descriptive of residual model of each variable

Residual of variable	Mean	Variance
Y1_1	-0.001	0.0234
Y1_2	0.081	0.3685
Y2_1	-0.037	0.2193
Y2_2	0.024	0.148
Y3	-0.002	0.0004
Y4	0.052	0.627

All quality characteristics are monitored simultaneously. Table 4 illustrates the correlation among the six residual variables.

Multivariate T^2 Hotelling control chart

Multivariate T^2 Hotelling control chart is constructed. Multivariate T^2 Hotelling control chart for original data with upper control limit (UCL) value equal to 29.2 is illustrates in figure 5(a) showing that there were 50 instances where the mechanism failed, which shown by some points are out of control. There are oscillating and it fails out at points particularly after sample 157th. This behavior comes from the dependence of measurements over the time on original data. Instead, by using residual data, the number out-of-control samples decreases down to 9 samples. Multivariate T^2 Hotteling control chart using residual data is more stable than multivariate T^2 Hottelling control chart using original data, as shown in Figure 5(b).

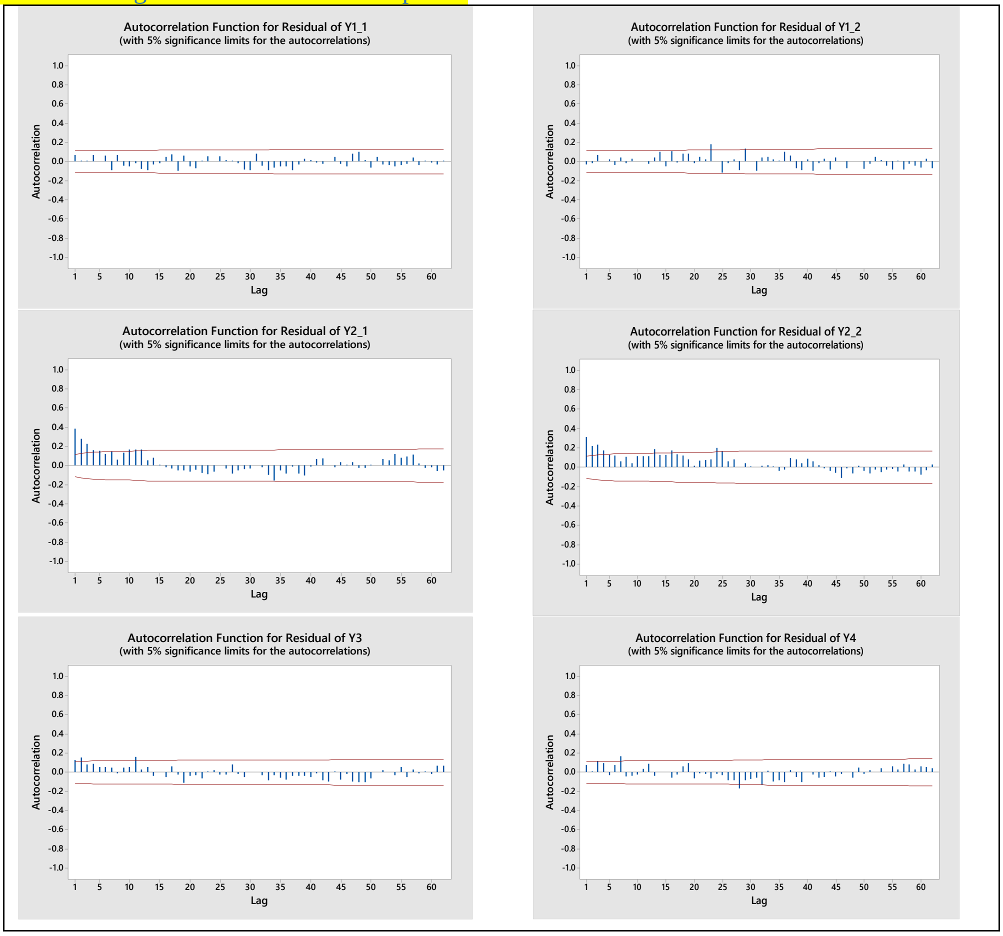
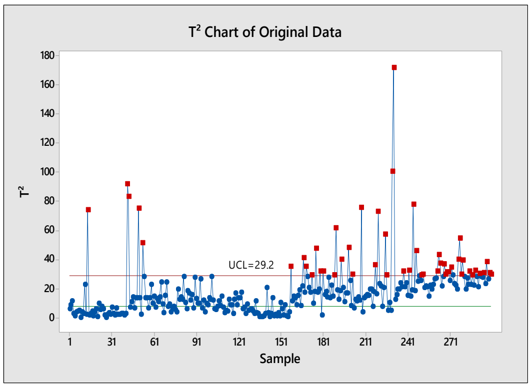


Figure 4. Autocorrelation test of each residual variable

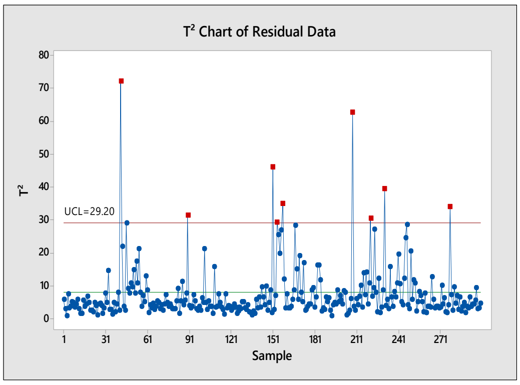
Table 4. Correlation test between residual variables

Characteristics \ Variables		Residual of Y1_1	Residual of Y1_2	Residual of Y2_1	Residual of Y2_2	Residual of Y3
Residual of Y1_2	Correlation	0.046				
	P-Value	0.431				
Residual of Y2_1	Correlation	-0.092	0.064			
	P-Value	0.111	0.266			
Residual of Y2_2	Correlation	0.105	0.112	-0.019		
	P-Value	0.069	0.052	0.743		
Residual of Y3	Correlation	0.189	0.087	0.035	0.064	
	P-Value	**0.001***	0.133	0.542	0.268	
Residual of Y4	Correlation	0.272	0.033	0.131	-0.014	0.144
	P-Value	**0.000***	0.571	**0.023***	0.808	**0.013***

Note: *) at 5% significance level



(a) by original data



(b) by residual data

Figure 5. T^2-Hotteling Multivariate control chart

Decomposition is a valuable diagnostic technique for identifying out-of-control signals in multivariate control charts, particularly in T2 Hotelling charts. It breaks down the T2 statistic into components that represent the contribution of each individual variable to the out-of-control signal. This approach involves estimating values d_i for each variable and focusing on those variables where d_i) values are relatively large. Table 5 typically displays the variables with the highest d_i values, indicating which variables contribute most significantly to the out-of-control signals detected in the multivariate T^2 Hotelling control chart. This helps pinpoint specific factors or characteristics that may need attention or correction in the manufacturing or process control environment. Y1_2, Y2_1, and Y3 are responsible for out-of-control signals on sample 231st, 154th, and 42nd, respectively. Y1_1 is responsible for samples 90th and 278th. Y2_2 is responsible for samples 208th and 221st. Y4 is responsible for samples 151st and 158th.

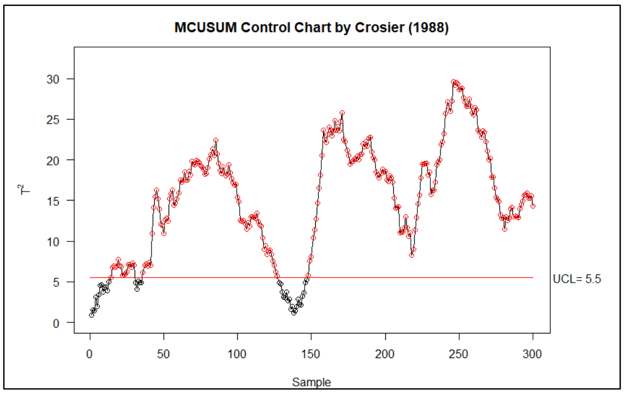
Table 5. Decomposed T^2 Hotteling value

Sample	Variables					
	Y1_1	Y1_2	Y2_1	Y2_2	Y3	Y4
42	11.44	0.922	3.919	0.756	41.316	3.766
90	14.47	0.187	0.007	4.659	0.518	4.742
151	0.033	0.726	0.312	0.115	1.314	39.02
154	10.73	0.390	15.44	2.142	0.145	0.559
158	1.450	0.622	7.821	0.239	0.044	19.47
208	5.918	8.376	0.967	40.04	1.127	1.883
221	0.066	0.101	4.608	26.74	1.552	0.113
231	3.693	24.50	0.721	2.862	7.022	0.302
278	21.09	1.052	0.119	0.005	2.198	3.815

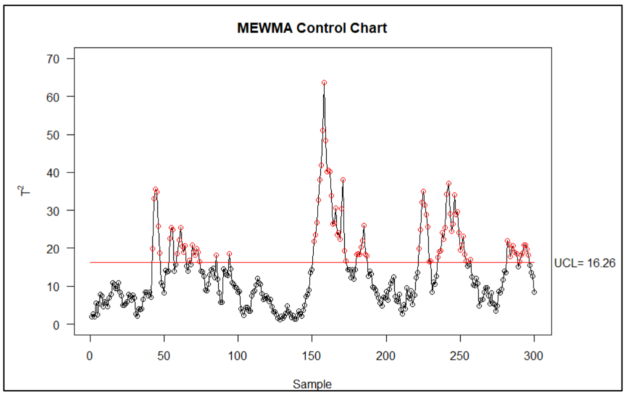
MCUSUM and MEWMA control chart

In Rstudio (2020), the MCUSUM and MEWMA control charts were implemented using the MSQC package. The charts were configured with parameters including ARL0 = 200 (corresponding to a false alarm rate α = 0.05), reference value k = 0.5, and decision limit h = 5.5. The MCUSUM control chart, applied to residual data, demonstrates enhanced sensitivity in detecting small changes in the mean vector of the process compared to the multivariate T^2 Hotelling control charts under identical conditions (p = 6; n = 1 and ARL_0 = 200), as illustrated in Figure 6(a). For instance, while the first signal in the multivariate T^2 Hotelling chart appears at sample 42, the MCUSUM chart detects the first signal at sample 14. Conversely, Figure 6(b) illustrates that the MEWMA control chart exhibits comparable sensitivity to the multivariate T^2 Hotelling control chart in detecting process changes. This comparison highlights the effectiveness of MCUSUM and MEWMA charts in differentiating their capabilities in sensitivity relative to traditional T^2 Hotelling control charts in process monitoring and quality control scenarios.

Implementing T^2 Hotteling control chart, MCUSUM chart and MEWMA chart for the obtained residual data can overcome multivariate autocorrelated data effectively. When compared with MCUSUM and MEWMA, T^2 Hotteling has better performance in detecting small shifts in the process. Meanwhile, the MCUSUM residual chart and the MEWMA residual chart show a large shift from the average. In addition, T^2 Hotteling also shows stable shifts around the average. However, the MCUSUM chart and the MEWMA chart show oscillations in shifts and even show a trend. This shows that the T^2 Hotteling residual chart has better performance than the MCUSUM and MEWMA residual control charts.



(a) MCUSUM control chart



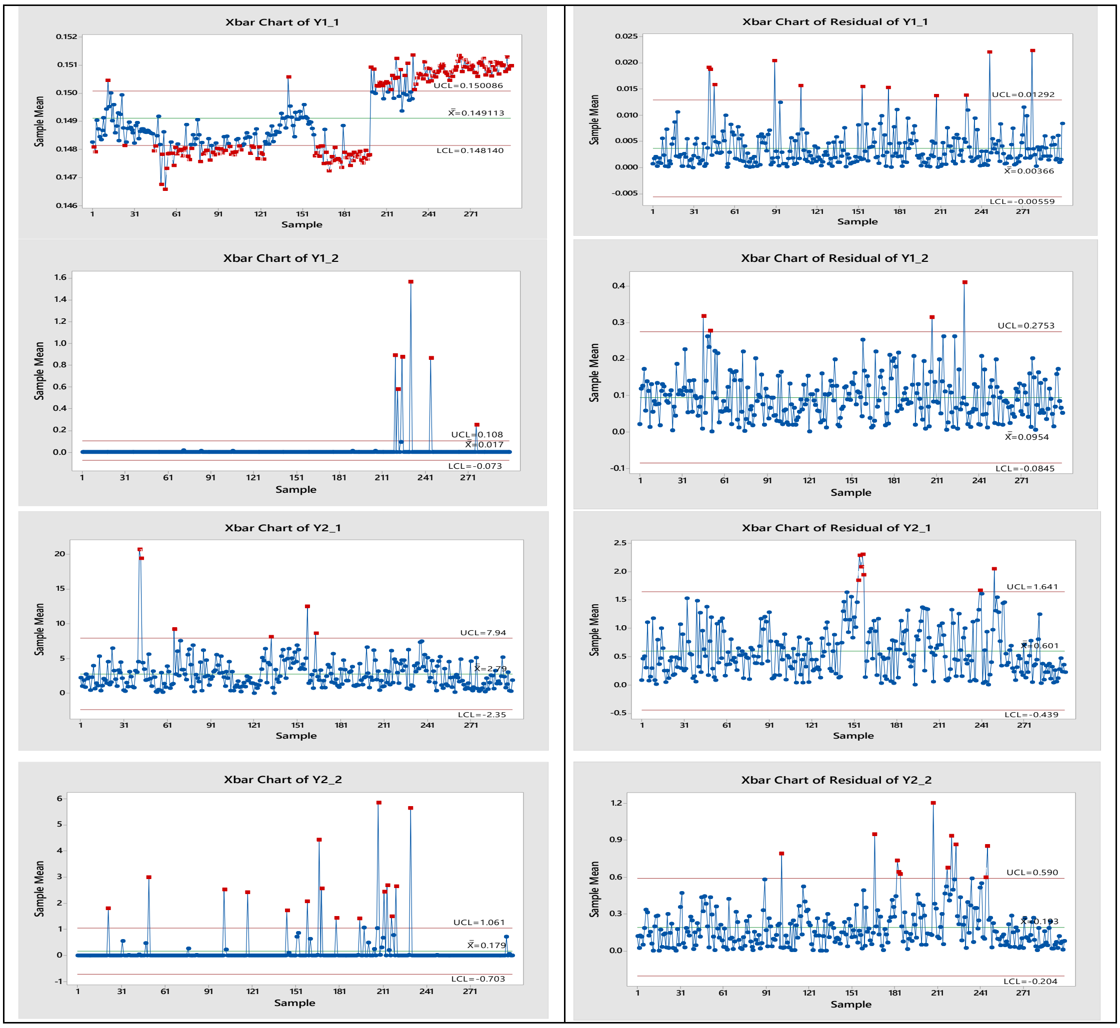
(b) MEWMA control chart

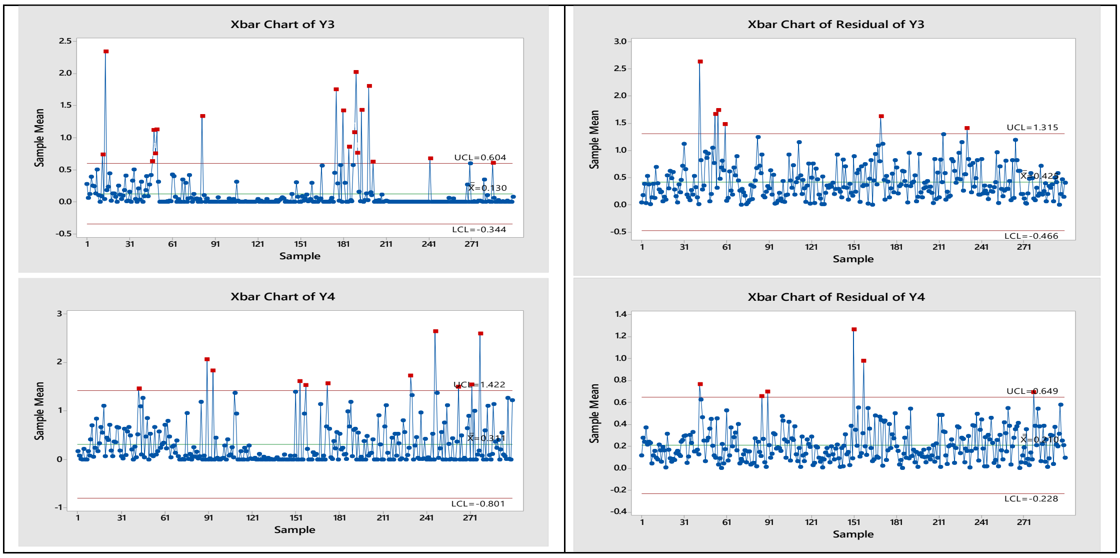
Figure 6. Multivariate control charts using residuals data

4.3. Comparison univariate control chart between original and residual data

In this section, Figure 7 presents a comparison between univariate control charts based on original data and residual data. The findings illustrate that the residual control chart outperforms the original data-based chart, particularly when the original data exhibit significant time series effects indicated by high autocorrelation. Specifically, Figure 7 demonstrates that control charts based on the original data exhibit more instances of out-of-control signals compared to those based on residual data. This indicates that using residuals, which account for the modeled effects and reduce autocorrelation, leads to improved performance in detecting deviations from the expected process behavior. Thus, employing residual-based control charts can enhance the accuracy and reliability of quality control measures in manufacturing or other monitored processes. Using three times of standard deviation from the center line rules, based on original data control chart, there are 181 samples, 6 samples, 6 samples, 16 samples, 18 samples, and 11 samples are out-of-control for each variable Y1_1, Y1_2, Y2_1, Y2_2, Y3 and Y4; respectively. Otherwise, using the same rules for testing, based on the residual data control chart, number of samples out of control decreasing into 11 samples, 4 samples, 7 samples, 11 samples, 6 samples and 6 samples for each variable Y1_1, Y1_2, Y2_1, Y2_2, Y3 and Y4; respectively. Even though variable Y2_1 has increasing number of samples out of control in residual data control chat, but there five consecutive points of out-of-control samples are getting large shift from the centerline.

The overall impression of process stability shown by control charts using residual data are rather different than was obtained from the control charts based on the original data. Otherwise, univariate control chart by original data for each variable, the pattern also shows the trend and large shift from the average. It might cause by the autocorrelation effects that happened on original data. As shown by the Figure 3, we see that the autocorrelation effect of the original data is very high which shown by the significant lag.





(a) (b)

Figure 7. Univariate control chart: (a) $\bar{x}$ control chart of original data; (b) $\bar{x}$ control chart of residual data

To address the practical implications of our proposed model in a real-world manufacturing context, we emphasize several key benefits. Firstly, the MAR-ANN model enhances detection sensitivity, enabling the early identification of potential quality issues. This allows for prompt corrective actions, reducing the incidence of defective products and minimizing rework, ultimately enhancing overall product quality. Additionally, the model effectively handles autocorrelation, a common challenge in traditional control charts, ensuring more reliable monitoring and reducing false alarms. This reliability is crucial for maintaining consistent product quality in continuous-flow manufacturing processes. Furthermore, our model is scalable and adaptable to various manufacturing processes with complex, multivariate, and autocorrelated data, making it suitable for diverse industries, from electronics to automotive. The implementation can be seamlessly integrated with existing manufacturing execution systems (MES) and statistical process control (SPC) software, allowing manufacturers to leverage advanced analytics without overhauling their current systems. This integration, coupled with the model's ability to lower operational costs by improving detection of process deviations and reducing false alarms, highlights its economic impact. Additionally, successful implementation requires comprehensive training for operators and engineers, demonstrating the model's benefits in improving process control and reducing false alarms. By promoting a culture of continuous improvement, manufacturers can use insights gained from the model to refine their processes continuously and maintain a competitive edge.

5. CONCLUSION

The case study examined in this paper reveals that the test of autocorrelation and the analysis of the time series are critical preliminary steps in the application of control charts. The performance of control charts is deteriorated by auto-correlated observations. As observed in charts built using original data, it increases the false alarm rate. It should also be noted that in applying multivariate control charts the existence of auto-correlated observations may mask the actual correlation between variables. Moreover, dependency among the variables also has effect to the performance of univariate control chart. Hence, it is better using multivariate control chart. Therefore, it is recommended to use MAR model using ANN approach to reduce autocorrelation effect on multivariate data.

In order to identify out-of-control signals in multivariate control charts, it is possible to use univariate control charts as it is easy to implement. However, in cases associated with actual correlation among variables, the univariate control charts can result in misleading conclusions. Instead, decomposing statistics is a suitable technique that can be used in T^2 Hotteling multivariate control charts to identify the contribution of variables in out-of-control signals. The residual control charts, derived from the ANN-based model, perform significantly better in detecting mean shifts. This improvement is particularly evident in terms of sensitivity, where residual control charts showed a higher capability in identifying small process changes compared to traditional control charts. By emphasizing the practical benefits of residual control charts in handling autocorrelated multivariate data, our study contributes to the field by showcasing an effective solution for improved process monitoring and quality control. This approach offers valuable insights and practical implications for practitioners aiming to enhance their process control systems.

Based on the analysis of the case study, it is evident that in scenarios where detecting small changes in process parameters is critical, MCUSUM and MEWMA charts offer advantages over the T^2 Hotelling control chart. These alternative control charts exhibit superior run length performance and greater sensitivity in detecting minor shifts in the process's mean vector. This heightened sensitivity enables quicker response and action in maintaining process quality and efficiency. Given that the data in this study were derived from product specifications measured by an AOI system, which operates on numerical values, an intriguing area for future research involves exploring the application of P control charts. P control charts are pertinent for monitoring defect proportions and could provide valuable insights when applied to control charts using image data as input. Analyzing and interpreting control charts with image data presents a promising avenue to enhance quality control methodologies, particularly in sectors reliant on visual inspection and image-based measurements. This potential research direction could further advance understanding and implementation of robust quality control strategies in manufacturing and related industries.

In future studies, we aim to investigate the optimal selection and sensitivity of ANN models for handling multivariate time series data in industrial processes. This will involve conducting comprehensive experiments to compare various ANN architectures (e.g., MLP, RNN, LSTM, GRU) and configurations (e.g., number of layers, neurons per layer, activation functions) to identify the most suitable models. Additionally, we will perform a sensitivity analysis by systematically varying key ANN parameters such as learning rate, hidden layer sizes, and regularization terms, as well as introducing variations in data quality like noise and missing data. By evaluating the impact of these changes on performance metrics, we intend to determine the robustness and stability of the ANN models and identify the configurations that produce the most representative and reliable residuals for process monitoring. This research will provide deeper insights into optimizing ANN models, enhancing the effectiveness of residual control charts, and offering valuable guidance for practitioners and researchers in improving industrial process monitoring and quality control.

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Auto-correlated Multivariate Quality Control for Electronic Products Manufacturing with Decomposition Analysis

Responses to the Reviewers

The authors gratefully acknowledge the comments and suggestions of the reviewers. In the revision, we have made major changes on our article to consider all the questions raised by the reviewers. This revision includes modifications to the original contents and the clarifications of the questions, managerial implications, and references to recent articles in Mathematical Modelling of Engineering Problems. We highlight the changes to our manuscript within the document by using colored text. The following are our detailed responses to the referees.

Responses to the Reviewer #1

1. The paper is generally well-structured, but some sections require better organization to enhance readability and coherence. For instance, the introduction could more explicitly state the research gaps and how this paper aims to fill them.

   Response: Thank you for your constructive feedback. We understand the importance of clearly stating the research gaps and the objectives of the paper in the introduction. Based on your suggestion, we have revised the introduction to explicitly highlight the research gaps and articulate how this paper aims to address them. Below is the updated section of the introduction:

   > The requirements of product inspection have become more challenging as product attributes become complex and increasingly correlated over time. Statistical process monitoring (SPM) is a crucial tool in quality control, but traditional SPM systems face significant challenges in modern electronic product manufacturing. One major issue is that traditional control charts assume data is independently distributed, which is often violated due to autocorrelation, leading to instability, and increased false alarms. Additionally, traditional control charts are not designed to handle multiple interrelated quality attributes simultaneously, which can mislead quality decisions and reduce the ability to detect process changes. These challenges

have resulted in a low adoption of control charts in continuous-flow systems. This paper aims to address these gaps by proposing advanced SPM techniques that account for autocorrelation and introducing multivariate-based quality control methods to handle interrelated attributes simultaneously. Through these enhancements, we seek to increase the reliability and practical utility of control charts, encouraging their broader adoption in the electronic product manufacturing industry.

2. The abstract provides a good summary of the paper but could include a brief mention of the key findings and implications to strengthen its impact.

Response: Thank you for your valuable suggestion. We agree that including key findings and implications in the abstract would strengthen its impact. Based on your feedback, we have revised the abstract to highlight the main outcomes and their significance. Below is the updated abstract:

Updated Abstract:

Most modern industrial process outcomes are multivariate, and univariate control charts can lead to misleading conclusions in the case of high correlation among variables. This paper presents a novel multivariate statistical process control method to monitor electronic products with multivariate correlated outcomes. We develop a procedure for monitoring multivariate autocorrelated data using a multivariate autoregressive (MAR) model with neural networks. This study investigates the significance and sensitivity of using MCUSUM, MEWMA, and T2 Hotelling charts to detect small changes in the mean vector of a process. The identification of out-of-control signals generated from multivariate statistical process control is derived from univariate charts and a decomposition approach. Our proposed decomposing statistics determine the contribution of variables in out-of-control signals by T2 Hotelling multivariate control charts. Additionally, MCUSUM and MEWMA control charts demonstrate good run length performance and high sensitivity in detecting small changes in the process's mean vector, enabling prompt corrective actions. These findings suggest that the proposed method enhances the reliability and responsiveness of quality control in electronic product manufacturing.

3. The literature review is comprehensive; however, it mostly lists previous works without critically analyzing or comparing these methods in detail. A deeper analysis of how the proposed ANN-based model differs or improves upon existing methods would be beneficial.
   Response: Thank you for your insightful feedback. We agree that a deeper analysis and comparison of existing methods with our proposed ANN-based model would enhance the literature review and provide a clearer understanding of its contributions. Based on your suggestion, we have revised the literature review to include a more critical analysis and detailed comparison. We have revised in sub section 2.4 Summary.

   Traditional methods often assume independence between observations, which is violated in continuous-flow manufacturing processes due to autocorrelation. This violation leads to increased false alarm rates and reduced average run length (ARL). While multivariate control charts address correlation among variables, they can be complex and computationally intensive, and they may not effectively identify specific variable contributions in out-of-control signals. Our proposed ANN-based model addresses these limitations by integrating a multivariate autoregressive (MAR) approach with neural networks, improving sensitivity to small shifts in the process mean vector and enhancing robustness to autocorrelation. The model offers better detection capabilities, reducing false alarms and improving ARL stability. Additionally, it provides detailed decomposition of out-of-control signals, allowing process engineers to pinpoint and address root causes of variations more effectively. These improvements enhance the reliability and practicality of SPM systems in modern manufacturing, leading to more timely and accurate quality control interventions, ultimately improving product quality and manufacturing efficiency.

4. Include more recent studies to ensure that the review is up to date, as this field is rapidly evolving.

   Response: Thank you for highlighting the importance of including recent studies in our literature review. We agree that staying current with the latest developments in this rapidly evolving field is crucial. Based on your suggestion, we have reviewed and incorporated several recent studies that contribute to the understanding and advancement of statistical process monitoring (SPM) and neural network-based models for quality control.

   1. Yang, C. L., & Sutrisno, H. (2021). Reducing response delay in multivariate process monitoring by a stacked long-short term memory network and real-time contrasts. *Computers & Industrial Engineering*, *153*, 107052.
   2. Wang, K. J., & Asrini, L. J. (2022). Deep learning-based automatic optical inspection system empowered by online multivariate autocorrelated process control. *The International Journal of Advanced Manufacturing Technology*, *120*(9), 6143-6162.

5. The introduction provides good background but does not sufficiently highlight the specific gaps in the literature or limitations of existing methods that this work aims to address. Please expand the introduction to clearly state the issues with current multivariate autocorrelated process monitoring approaches that this study seeks to overcome.

   Response: Thank you for your insightful feedback. We agree that the introduction should more explicitly state the research gaps and limitations of existing methods that our study addresses. Based on your suggestion, we have revised the introduction to highlight these aspects clearly.

   Traditional SPM methods, such as Shewhart, CUSUM, and EWMA control charts, assume that process data is independently distributed over time. However, this assumption is often violated in modern manufacturing environments where autocorrelation is prevalent. The violation of the independence assumption leads to several issues with traditional control charts: increased false alarms, decreased sensitivity, and complexity in handling multivariate data. Existing multivariate control charts, such as T^2 Hotelling's, MCUSUM, and MEWMA, address these correlations but are often complex to implement and may not effectively decompose out-of-control signals to identify specific variable contributions.

To address these limitations, our study proposes a novel ANN-based multivariate statistical process control model that integrates a multivariate autoregressive (MAR) approach with neural networks. This model aims to enhance detection sensitivity, improve robustness to autocorrelation, and provide detailed decomposition of out-of-control signals. By leveraging the capabilities of neural networks, our model improves sensitivity to small shifts in the process mean vector, ensuring timely detection of quality issues. The integration of MAR with neural networks effectively manages autocorrelated data, reducing false alarms and improving the stability of Average Run Length (ARL). Additionally, our model offers a detailed decomposition of out-of-control signals, using univariate charts and a decomposition approach to identify specific variable contributions. This feature allows process engineers to pinpoint and address root causes of variations more accurately. By addressing these specific gaps and limitations in current multivariate autocorrelated process monitoring approaches, our study aims to enhance the reliability and practicality of SPM systems in modern manufacturing environments, ultimately improving product quality and manufacturing efficiency.

6. More details are needed on the data collection, manufacturing process, and variables measured. Things like measurement accuracy, instrumentation calibration, data preprocessing, etc. should be discussed to provide context.

   Response: Thank you for your valuable feedback. We agree that providing more details on the data collection, manufacturing process, and variables measured is crucial for the context and robustness of our study. We have revised the relevant section to include these details.

   To ensure the accuracy and reliability of our study, we collected data from a continuous-flow electronic product manufacturing process. This process involves multiple stages, including assembly, soldering, testing, and packaging. The quality attributes measured at each stage are critical for maintaining high product standards.

This study implements the proposed MAR-ANN model for electronics products. The target manufacturing process of the product includes stamping, electroplating, injection molding, assembling, and packaging, as shown in Figure 2. The high-speed continuous production line possesses multivariate and autocorrelated properties. An automatic optic inspection (AOI) system is installed in the process. The data collection was conducted using high-precision instruments that were regularly calibrated to ensure measurement accuracy. Instruments such as digital calipers, micrometers, and automated optical inspection (AOI) systems were employed to measure dimensions. The product feature measurements are recorded by AOI. An automatic optic inspection (AOI) system is installed in the process to measure product features. The proposed MAR-ANN model allows the quality defects to be easily detected.

Defect types of “overflowed”, “extra-materials” and “metal debris” are key items, which are detected by AOI. The specification measured by AOI system is based on the numerical value, such as length, width, and area. In this study, six features are controlled for each product. Table 1 explains the description of each variable. The products are measured by batches, each containing 100 units of product. This study collects 300 batches as the samples for the MAR-ANN control chart.

7. The proposed MAR-ANN methodology requires more specifics on model selection, optimization, and validation to demonstrate its appropriateness. Details on training, validation, hyperparameter selection, and performance metrics should be added.

Response: Thank you for your valuable feedback. We agree that providing more details on the MAR-ANN methodology is crucial to demonstrate its appropriateness. We have revised the relevant section to include these details.

The proposed methodology integrates a Multivariate Autoregressive (MAR) model with an Artificial Neural Network (ANN) to handle the complexities of autocorrelated and multivariate quality data. The MAR model captures the time-series characteristics and dependencies among variables, while the ANN addresses the nonlinear relationships and enhances the sensitivity to small shifts in the process mean vector. The MAR-ANN model was trained using a dataset collected from a continuous-flow electronic product manufacturing process. The dataset was split into training (70%), validation (15%), and test (15%) sets to ensure the robustness of the model. The training set was used to fit the model, the validation set was used to fine-tune hyperparameters, and the test set was used to evaluate the model's performance. Hyperparameter selection is critical for optimizing the performance of the ANN. We used a grid search approach to determine the optimal hyperparameters, including the number of hidden layers, the number of neurons per layer, learning rate, and regularization parameters. The grid search was performed using cross-validation on the training set, and the combination of hyperparameters that yielded the best performance on the validation set was selected for the final model.

8. The description of the ANN model and its configuration (such as architecture, training data, and hyperparameters) is vague. A more detailed explanation is necessary to allow reproducibility and to assess the appropriateness of the chosen techniques.

   Response: Thank you for your valuable feedback. We have revised the relevant section to include detailed specifics on the ANN model configuration using the MLPRegressor. The model, trained on 14,000 observations from an electronic product manufacturing process, includes a single hidden layer with 50 neurons and uses the 'relu' activation function. Key hyperparameters include an alpha of 0.0001 for regularization, a learning rate of 0.001, and the Adam optimizer. The model underwent up to 1000 iterations, with early stopping disabled, and employed cross-validation (70% training, 15% validation, 15% test split). These details ensure the model's reproducibility and highlight the robustness and appropriateness of our approach.

9. The statistical validation of the model needs to be more robust. Consider adding more metrics for performance evaluation and comparing these with traditional multivariate quality control charts.

   Response: We appreciate the suggestion to enhance the robustness of our model's statistical validation. To address the challenge of autocorrelation, which traditional multivariate control charts cannot effectively manage, we employed residual-based control charts. This method involves modeling the autocorrelation structure of the process data using our MAR-ANN approach and then applying control charts to the residuals, which are assumed to be independent and identically distributed. By using residual-based control charts, we can effectively detect shifts in the process mean while accounting for autocorrelation, thus improving the accuracy and reliability of the monitoring system. We used Average Run Length (ARL) as performance metrics. Moreover, we compare the performance of our proposed MAR-ANN methodology with traditional multivariate control charts like MCUSUM, MEWMA, and Hotelling's T^2. This comparison includes analyzing detection times, sensitivity to small mean shifts, and overall accuracy in identifying out-of-control signals. The results demonstrate that our residual-based approach effectively handles autocorrelation and outperforms conventional methods in detecting process anomalies. In summary, by using residual-based control charts and incorporating a diverse set of performance metrics, we have strengthened the robustness of our model's statistical validation, showcasing its superiority over traditional methods in handling autocorrelated multivariate process data.

10. While the results indicate that the proposed model performs well, the discussion lacks depth in terms of interpreting these results in the context of manufacturing realities. Discuss the practical implications of implementing this model in a real-world setting.

    Response: Thank you for your valuable feedback. To address the practical implications of our proposed model in a real-world manufacturing context, we emphasize several key benefits. Firstly, the MAR-ANN model enhances detection sensitivity, enabling the early identification of potential quality issues. This allows for prompt corrective actions, reducing the incidence of defective products and minimizing rework, ultimately enhancing overall product quality. Additionally, the model effectively handles autocorrelation, a common challenge in traditional control charts, ensuring more reliable monitoring and reducing false alarms. This reliability is crucial for maintaining consistent product quality in continuous-flow manufacturing processes. Furthermore, our model is scalable and adaptable to various manufacturing processes with complex, multivariate, and autocorrelated data, making it suitable for diverse industries, from electronics to automotive. The implementation can be seamlessly integrated with existing manufacturing execution systems (MES) and statistical process control (SPC) software, allowing manufacturers to leverage advanced analytics without overhauling their current systems. This integration, coupled with the model's ability to lower operational costs by improving detection of process deviations and reducing false alarms, highlights its economic impact. Additionally, successful implementation requires comprehensive training for operators and engineers, demonstrating the model's benefits in improving process control and reducing false alarms. By promoting a culture of continuous improvement, manufacturers can use insights gained from the model to refine their processes continuously and maintain a competitive edge.

11. The sensitivity analysis of the model to changes in its parameters or variations in data quality could enhance the paper's contribution to the field.

    Response: We appreciate the suggestion to include a sensitivity analysis. However, in this study, the primary objective of using the ANN model was to effectively handle multivariate time series data. Our focus was on demonstrating the superiority of residual control charts over traditional control charts in terms of sensitivity to mean shifts. While we did not conduct a detailed sensitivity analysis of the ANN model's parameters, we provided a comprehensive comparison between traditional control charts and residual control charts. Our findings indicate that residual control charts, derived from the ANN-based model, perform significantly better in detecting mean shifts. This improvement is particularly evident in terms of sensitivity, where residual control charts showed a higher capability in identifying small process changes compared to traditional control charts. By emphasizing the practical benefits of residual control charts in handling autocorrelated multivariate data, our study contributes to the field by showcasing an effective solution for improved process monitoring and quality control. We believe this approach offers valuable insights and practical implications for practitioners aiming to enhance their process control systems.

We added in the future research regarding your suggestion as follows:

In future studies, we aim to investigate the optimal selection and sensitivity of ANN models for handling multivariate time series data in industrial processes. This will involve conducting comprehensive experiments to compare various ANN architectures (e.g., MLP, RNN, LSTM, GRU) and configurations (e.g., number of layers, neurons per layer, activation functions) to identify the most suitable models. Additionally, we will perform a sensitivity analysis by systematically varying key ANN parameters such as learning rate, hidden layer sizes, and regularization terms, as well as introducing variations in data quality like noise and missing data. By evaluating the impact of these changes on performance metrics, we intend to determine the robustness and stability of the ANN models and identify the configurations that produce the most representative and reliable residuals for process monitoring. This research will provide deeper insights into optimizing ANN models, enhancing the effectiveness of residual control charts, and offering valuable guidance for practitioners and researchers in improving industrial process monitoring and quality control.

12. It would benefit from greater clarity and cohesion in conclusion. Specifically, it could enhance its effectiveness by clearly quantifying the comparative analysis of different control charts and explicitly linking these findings to the supporting data presented earlier in the paper. **Response:** We acknowledge the need for greater clarity and cohesion in the conclusion section of our paper. In response, we revised the conclusion to provide a more explicit and quantified comparative analysis of the different control charts discussed in our study. Specifically, we highlight key performance metrics such as detection sensitivity, false alarm rates, and Average Run Length (ARL) for each control chart method, including traditional control charts and the proposed residual-based control charts. Additionally, we will clearly link these comparative findings to the supporting data presented earlier in the paper, ensuring that the results are directly tied to the empirical evidence. By doing so, we aim to reinforce the significance of our findings and provide a more coherent and impactful conclusion that effectively summarizes the contributions of our research. This revised conclusion will offer a clear, quantified comparison of the control charts, underscoring the practical advantages of

the residual-based approach in handling autocorrelated multivariate data, and providing valuable insights for practitioners in the field of industrial process monitoring and quality control.

13. The reference format generally meets journal requirements, but some references are outdated. It is recommended to include more recent research findings, all of which should have a DOI or be searchable on Google.

    Response: We appreciate your observation regarding the need for more recent references. To address this, we updated our literature review and reference list to include the latest research findings in the field of multivariate statistical process control and ANN-based models. We ensure that all new references are current, have a DOI, or are easily searchable on Google.

Responses to the Reviewer #1

1. The literature review section needs to be strengthened. While it covers key topics like multivariate auto-correlated control charts, residual control charts, and applying ANN to statistical process monitoring (SPM), the synthesis and critical analysis of prior work is lacking. The authors should identify specific gaps in the existing research that their proposed methodology aims to address. This will help position the novelty and significance of their work more clearly.

   Response: We appreciate your suggestion to enhance the literature review section. To address this, we will revise the literature review to include a more thorough synthesis and critical analysis of prior work. Specifically, we revised in introduction and in literature review sub section 2.4. (we highlighted the revision with blue color).

2. The methodology description requires more details for reproducibility. Equations are provided for the MAR model and residual calculations, but the explanations around them are brief. Elaborate on the ANN architecture (number of layers, nodes, activation functions, etc.) and training process used. Specify hyperparameter settings. The procedure diagram in Figure 1 is helpful, but the steps need to be described in greater depth in the text.

Response: We acknowledge the need for a more detailed and comprehensive description of the methodology to ensure reproducibility. To address this, the architecture of ANN we elaborated in section 4.2.2 as follows:

> The specific ANN model that used to figure out the autoregressive model with 6 variables and order $p = 16$ in this case is MLPRegressor. The model, trained on 14,000 observations from an electronic product manufacturing process, includes a single hidden layer with 50 neurons and uses the 'relu' activation function. Key hyperparameters include an alpha of 0.0001 for regularization, a learning rate of 0.001, and the Adam optimizer. The model underwent up to 1000 iterations, with early stopping disabled, and employed cross-validation (70% training, 15% validation, 15% test split). These details ensure the model's reproducibility and highlight the robustness and appropriateness of our approach.

3. The results focus heavily on qualitative interpretations of control chart patterns. Please add more quantitative analysis and numerical comparisons of method performance, such as false alarm rates, out-of-control run lengths, and fault detection rates.

   Response: We appreciate your suggestion to include more quantitative analysis in the results section. To address this, we revised the results section to provide a comprehensive evaluation of our method's performance through the following quantitative metrics: page 7-9 sub section T2 Hotteling, Mcusum and MEWMA control chart. We highlight with font color blue.

4. Discussion of results should include more interpretation rather than just presentation. What are the key insights and practical implications? How generalizable is the approach to other manufacturing contexts? Acknowledge any limitations of the method and scope for future enhancements.

   Response: We appreciate your suggestion to enhance the discussion section. To address this, we will revise the discussion as follows:

   > To address the practical implications of our proposed model in a real-world manufacturing context, we emphasize several key benefits. Firstly, the MAR-ANN model enhances detection sensitivity, enabling the early identification of potential quality issues. This allows for prompt corrective actions, reducing the incidence of defective products and

minimizing rework, ultimately enhancing overall product quality. Additionally, the model effectively handles autocorrelation, a common challenge in traditional control charts, ensuring more reliable monitoring and reducing false alarms. This reliability is crucial for maintaining consistent product quality in continuous-flow manufacturing processes. Furthermore, our model is scalable and adaptable to various manufacturing processes with complex, multivariate, and autocorrelated data, making it suitable for diverse industries, from electronics to automotive. The implementation can be seamlessly integrated with existing manufacturing execution systems (MES) and statistical process control (SPC) software, allowing manufacturers to leverage advanced analytics without overhauling their current systems. This integration, coupled with the model's ability to lower operational costs by improving detection of process deviations and reducing false alarms, highlights its economic impact. Additionally, successful implementation requires comprehensive training for operators and engineers, demonstrating the model's benefits in improving process control and reducing false alarms. By promoting a culture of continuous improvement, manufacturers can use insights gained from the model to refine their processes continuously and maintain a competitive edge.

5. The conclusions are too broad and lacking specifics. Please provide more detailed and quantified conclusions on the performance of the proposed MAR-ANN approach compared to other methods.

   Response: We acknowledge the need for more detailed and quantified conclusions. We highlighted the revised version with font color blue in conclusion section.

   The residual control charts, derived from the ANN-based model, perform significantly better in detecting mean shifts. This improvement is particularly evident in terms of sensitivity, where residual control charts showed a higher capability in identifying small process changes compared to traditional control charts. By emphasizing the practical benefits of residual control charts in handling autocorrelated multivariate data, our study contributes to the field by showcasing an effective solution for improved process monitoring and quality control. This approach offers valuable insights and practical implications for practitioners aiming to enhance their process control systems.

Analyzing the results of the considered case study indicates that in situations where it is important to detect small changes in process parameters, the MCUSUM and MEWMA charts are alternatives to the T^2 Hotelling control chart. In such situations, these control charts have better run length performance and more sensitive than the T^2 Hotelling control chart to detect a small change in the process's mean vector, which allows faster action. Since the data that used in this study come from specification product measured by AOI system is based on numerical value, an interesting future research concerns of P control chart, which related to the defect proportion control chart, will be gave analysis and interpretation of control chart with image data as an input data.

In future studies, we aim to investigate the optimal selection and sensitivity of ANN models for handling multivariate time series data in industrial processes. This will involve conducting comprehensive experiments to compare various ANN architectures (e.g., MLP, RNN, LSTM, GRU) and configurations (e.g., number of layers, neurons per layer, activation functions) to identify the most suitable models. Additionally, we will perform a sensitivity analysis by systematically varying key ANN parameters such as learning rate, hidden layer sizes, and regularization terms, as well as introducing variations in data quality like noise and missing data. By evaluating the impact of these changes on performance metrics, we intend to determine the robustness and stability of the ANN models and identify the configurations that produce the most representative and reliable residuals for process monitoring. This research will provide deeper insights into optimizing ANN models, enhancing the effectiveness of residual control charts, and offering valuable guidance for practitioners and researchers in improving industrial process monitoring and quality control

6. Writing can be made more concise and clear in some parts, especially the introduction. Avoid redundant phrases. Use paragraphs effectively to separate key ideas. Check grammar, typos and formatting consistency thoroughly before resubmission.

   Response: We acknowledge the need to enhance the clarity and conciseness of our writing. To address this, we revised the introduction and other parts of the paper.

4. Paper accepted (24-06-2024)

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Acceptance Letter

Mathematical Modelling of Engineering Problems

July 24, 2024

Luh Juni Asrini

Department of Industrial Engineering,
Widya Mandala Surabaya Catholic University,
Surabaya 60114,
Indonesia

Dear Luh Juni Asrini, Dian Retno Sari Dewi, Irene Karijadi,

MS: Auto-correlated Multivariate Quality Control for Electronic Products Manufacturing with Decomposition Analysis

I am pleased to inform you that as per the recommendation of the editorial board, your above-mentioned manuscript has been accepted for publication in Mathematical Modelling of Engineering Problems (ISSN 2369-0739).

Please note the following points, and ensure compliance:

1) Page proofs of your paper will also be sent to you for minor corrections and approval.

2) Provide us with the institutional email addresses of all authors, or other business email addresses that can be found on Google. At the same time, please provide the ORCID numbers of all authors.

3) Provide the complete institutional information for all authors, including the college/department, university, city, postal code, and country.

4) The corresponding author would receive a PDF of the published paper.

5) After a paper has been accepted, it is not permissible to add, remove, or change the order of authors. (Exceptions can be made only if there are credible reasons, and it also requires an official stamped document from the relevant department of the author's institution, sent from an official email address.)

6) If plagiarism is detected in an author's paper, the paper will be retracted before publication and will not be published. The publication fee paid by the author will not be refunded. If plagiarism is discovered after publication, the paper will be retracted, and we will notify the author's institution. Furthermore, the publication fee will not be refunded.

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Yours sincerely,

Date: July 24, 2024
Place: Edmonton, Canada

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Gmail **D.N. Dian Retno Sari Dewi P. , ST., MT. <dianretnosd@ukwms.ac.id>**

Decisions on the paper submitted to MMEP MM 1

editor.mmep iieta.org <editor.mmep@iieta.org> Wed, Jul 24, 2024 at 2:45 PM
To: "juniasrini@ukwms.ac.id" <juniasrini@ukwms.ac.id>
Cc: "dianretnosd@ukwms.ac.id" <dianretnosd@ukwms.ac.id>

Dear author,

We have reached a decision regarding your submission to *Mathematical Modelling of Engineering Problems*,

Manuscript Title: **Auto-correlated Multivariate Quality Control for Electronic Products Manufacturing with Decomposition Analysis**

Manuscript ID: MMEP MM 1

Our decision is to: Accept Submission

Since the APC for MMEP 1 has been completed in advance by Prof. Dian Retno Sari Dewi, and requested by Prof. Dian Retno Sari Dewi, you do not need to complete MMEP MM 1 APC. Your paper MMEP MM 1 is sent for formatting and proofreading.

If you have any questions, please do not hesitate to contact us.

Kind regards,

MMEP Editorial Board

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Acceptance Letter

Mathematical Modelling of Engineering Problems

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5. Proofreading (07-08-2024)

Gmail **D.N. Dian Retno Sari Dewi P. , ST., MT. <dianretnosd@ukwms.ac.id>**

FW: Galley proof of MMEP MM 1 URGENT

editor.mmep iieta.org <editor.mmep@iieta.org> Thu, Aug 15, 2024 at 10:44 AM
To: "juniasrini@ukwms.ac.id" <juniasrini@ukwms.ac.id>, "dianretnosd@ukwms.ac.id" <dianretnosd@ukwms.ac.id>

Kind reminder.

From: editor.mmep iieta.org
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Subject: FW: Galley proof of MMEP MM 1 URGENT

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Please return the revised version to this e-mail before **10 August 2024**. Thus, we have enough time to process your manuscript in the next step.

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Best regards,

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6. Final Proofreading (20-09-2024)

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Re: Final proof of MMEP MM 1 URGENT

Luh Juni Asrini <juniasrini@ukwms.ac.id> Mon, Sep 23, 2024 at 1:33 PM
To: "editor.mmep iieta.org" <editor.mmep@iieta.org>
Cc: dianretnosd@ukwms.ac.id, irenekarijadi@ukwms.ac.id

Dear Editor,

Thank you for providing the final proof of our manuscript. I have reviewed the document carefully and confirm that no further corrections are needed at this stage. All names, affiliations, addresses, and symbols have been checked and found to be accurate.

I have cc'd my co-authors in this response to confirm their awareness of and contributions to the manuscript, as requested.

Additionally, I confirm that there are no conflicts of interest related to the content of this manuscript.

Please let me know if you require anything else from our side.

Best regards,

On Fri, Sep 20, 2024 at 6:29 PM editor.mmep iieta.org <editor.mmep@iieta.org> wrote:

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To: editor.mmep iieta.org <editor.mmep@iieta.org>
Subject: Re: URGENT REMINDER RE: URGENT FW: FW: Galley proof of MMEP MM 1 URGENT

Dear Editorial Team,

I hope this email finds you well. I am sorry for the late response and was made you remind me many times.

Thank you for repeatedly sending the galley proof of my manuscript and reminding me. I have carefully reviewed and revised the paper according to the comments and suggestions provided. The changes have been highlighted in the attached document, as requested.

Additionally, I have included notes for any corrections that required further clarification directly in the file.

Please find the revised version attached. Should you need any further adjustments or clarifications, feel free to reach out to me.

Thank you for your time, and I look forward to hearing from you soon.

Best regards,

Luh Juni Asrini

On Thu, Sep 19, 2024 at 10:35 AM editor.mmep iieta.org <editor.mmep@iieta.org> wrote:

> **From:** editor.mmep iieta.org
> **Sent:** Wednesday, September 18, 2024 7:10 PM
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> **From:** editor.mmep iieta.org
> **Sent:** Monday, September 9, 2024 3:09 PM
> **To:** 'Luh Juni Asrini' <juniasrini@ukwms.ac.id>
> **Subject:** RE: FW: Galley proof of MMEP MM 1 URGENT
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> Reminder
>
> **From:** Luh Juni Asrini <juniasrini@ukwms.ac.id>
> **Sent:** Thursday, August 15, 2024 9:26 PM
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> **Subject:** Re: FW: Galley proof of MMEP MM 1 URGENT

Dear Editorial Team,

Thank you for sending the galley proof of my manuscript "MM1". I have carefully reviewed the marked comments and will make the necessary revisions accordingly.

I understand the importance of meeting the deadline of August 10th. However, because of unforeseen circumstances related to my work and career development, I am asking for a postponement of the paper's publication to the next issue in September.

I apologize for any inconvenience this may cause and assure you that I am committed to delivering a high-quality revised manuscript. I will be sure to highlight all changes made and address all comments thoroughly.

Thank you for your understanding and consideration.

Sincerely,

Luh Juni Asrini

On Thu, Aug 15, 2024 at 10:45 AM editor.mmep iieta.org <editor.mmep@iieta.org> wrote:

> Kind reminder.
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> **From:** editor.mmep iieta.org
> **Sent:** Monday, August 12, 2024 5:53 PM
> **To:** 'juniasrini@ukwms.ac.id' <juniasrini@ukwms.ac.id>
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> **From:** editor.mmep iieta.org
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Auto-Correlated Multivariate Quality Control for Electronic Products Manufacturing with Decomposition Analysis

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ABSTRACT

Many modern industrial processes involve multiple quality measures, and using individual control charts for each measure can be misleading if these measures are highly related. This paper proposes a new method for statistically controlling electronic products with multiple, interconnected quality characteristics. The method utilizes a combined model: a multivariate autoregressive (MAR) model with neural networks, to handle the presence of both correlation and autocorrelation in the data. The study compares the effectiveness of MCUSUM, MEWMA, and T^2 Hotelling charts in detecting small shifts in the overall process quality. To pinpoint the specific variables causing out-of-control signals in the T^2 Hotelling chart, we introduce a novel decomposition technique. This technique allows us to identify which measures are contributing most to these signals. Additionally, the MCUSUM and MEWMA charts demonstrate excellent performance in detecting small quality changes, leading to faster corrective actions. Overall, these findings suggest that our proposed method can significantly improve the reliability and responsiveness of quality control in electronics manufacturing.

1. INTRODUCTION

The complexity and increasing correlation of product features over time have made the requirements of product inspection more difficult. Statistical process monitoring is a method of quality control since variability is a primary indication of poor quality [1]. In many continuous processes of the electronic device manufacturing business, statistical process monitoring (SPM) typically develops over time to handle auto-correlated, multivariate quality data. Any changes in a process that may be the consequence of unforeseen and uncontrollable factors can be quickly identified by an effective SPM system.

Traditional control charts relied on the idea that the process would be dispersed independently across time, but as electronic device manufacture has advanced, this assumption is no longer valid. Control charts are produced for variables that defy one of the primary assumptions, serial-sample independence, when autocorrelation is present. The average run length (ARL) and stability of the control charts are both impacted by the violating of the presumption of independence [2]. Furthermore, if there are too many false alarms, the process engineer may prefer to completely ignore the control charts or misidentify the true source of variation. This explains why control charts are used on continuous-flow systems very infrequently [3].

Due to the fact that the industry that manufactures electrical products typically bases its product quality on a number of interconnected quality criteria and variables, SPM is also faced with multivariate problems [4]. The statistical characteristics of classic control charts are greatly impacted by interrelated variables, which can also result in a notable rise in the average false alarm rate and a fall in the capacity to identify process changes. Applying univariate control charts to every variable has the potential to mislead in decisions about quality. Consequently, multivariate based quality control techniques needed to take such characteristics into account at the same time.

As electronic products become more intricate and their quality characteristics show stronger connections over time, ensuring proper inspection becomes increasingly difficult. Traditional statistical process monitoring (SPM) systems struggle to keep pace with these complexities in modern manufacturing. One major issue is that traditional control charts assume data is independently distributed, which is often violated due to autocorrelation, leading to instability, and increased false alarms. Additionally, traditional control charts are not designed to handle multiple interrelated quality attributes simultaneously, which can mislead quality decisions and reduce the ability to detect process changes. These challenges have resulted in a low adoption of control charts in continuous-flow systems. This paper aims to address these gaps by proposing advanced SPM techniques that account for autocorrelation and introducing multivariate-based quality control methods to handle interrelated attributes simultaneously. Through these enhancements, we seek to increase the reliability and practical utility of control charts, encouraging their broader adoption in the electronic product manufacturing industry.

Traditional SPM methods, such as Shewhart, CUSUM, and EWMA control charts, assume that process data is independently distributed over time. However, this assumption is often violated in modern manufacturing environments where autocorrelation is prevalent. The violation of the independence assumption leads to several issues with traditional control charts: increased false alarms, decreased sensitivity, and complexity in handling multivariate data. Existing multivariate control charts, such as T^2 Hotelling's, MCUSUM, and MEWMA, address these correlations but are often complex to implement and may not effectively decompose out-of-control signals to identify specific variable contributions.

To address these limitations, our study proposes a novel ANN-based multivariate statistical process control model that integrates a multivariate autoregressive (MAR) approach with neural networks. This model aims to enhance detection sensitivity, improve robustness to autocorrelation, and provide detailed decomposition of out-of-control signals. By leveraging the capabilities of neural networks, our model improves sensitivity to small shifts in the process mean vector, ensuring timely detection of quality issues. The integration of MAR with neural networks effectively manages autocorrelated data, reducing false alarms and improving the stability of average run length (ARL). Additionally, our model offers a detailed decomposition of out-of-control signals, using univariate charts and a decomposition approach to identify specific variable contributions. This feature allows process engineers to pinpoint and address root causes of variations more accurately. By addressing these specific gaps and limitations in current multivariate autocorrelated process monitoring approaches, our study aims to enhance the reliability and practicality of SPM systems in modern manufacturing environments, ultimately improving product quality and manufacturing efficiency.

The present study will address the auto-correlated, multivariate quality control for electronic product manufacturing. We propose a model based on ANN to predict and build the residual based control chart for multivariate data with autocorrelation order p (AR(p)) processes.

The rest of this paper is organized as following. Section 2 discusses relevant literature review, such as SPM of multivariate auto-correlated observations, multivariate control chart, and ANN for multivariate and auto-correlated observations. Section 3 details the research methodology including manufacturing process and research variables. Section 4 illustrates a practical application and discussion. Finally, conclusions are provided in Section 5.

2. LITERATURE REVIEW

2.1 Multivariate auto-correlated control charts

Many industrial processes, both continuous and batch operations, frequently exhibit autocorrelation in their data, leading to ongoing efforts to find solutions [5]. Studies by Loredo et al. [6] and Psarakis and Papaleonida [7] highlight that even minor autocorrelation can significantly disrupt traditional control charts, causing them to signal false alarms more often and miss actual process changes. One solution involves filtering out autocorrelation using time series models and focusing control charts on the resulting uncorrelated residuals. This approach allows standard control charts to function effectively, as demonstrated by Callao and Rius [8] with their AR (1) model-based residual control charts. The concept can be extended beyond single variables. Issam and Mohamed [9] proposed using multivariate autoregressive (MAR) models to handle systems where multiple correlated variables exhibit serial dependence. Their work introduces an MAR control chart specifically designed for these multivariate autocorrelated processes. Their research proposed an MAR control chart for multivariate auto-correlated processes. For an MAR process with m variables, it is denoted by $\boldsymbol{x_t} = (\boldsymbol{x_{1t}}, \boldsymbol{x_{2t}}, \dots, \boldsymbol{x_{mt}})$ as a (m×1) vector.

Psarakis and Papaleonida [7] explained that shifts in the mean or variance of residuals signal changes in the actual process's mean or variance. By plotting residuals on a control chart, shifts in the process can be detected. The principle of residual charts is that, with a correct time series model, residuals become independently and identically distributed random variables, satisfying traditional quality control criteria and enabling the use of standard SPC charts. Therefore, developing an accurate time series model for multivariate autocorrelated data is essential in statistical process control. Although the ARIMA model is widely used for linear time series prediction, it struggles to capture nonlinear patterns.

Autocorrelation in process data is a persistent challenge, prompting researchers to develop solutions. Alwan and Roberts [10] addressed this issue by proposing residual-based control charts, which rely on data where autocorrelation has been removed. Woodall and Faltin [11] investigated the impact of self-correlation on control charts and explored various strategies to manage it. Their work included developing methods like the CUSUM control chart specifically designed for autocorrelated data [12-14]. Additionally, researchers have explored using exponentially weighted moving average (EWMA) control charts for data with autocorrelation [15-18].

A range of multivariate control charts exist in the literature, including T2 Hotelling, multivariate CUSUM (MCUSUM), and multivariate EWMA charts [19-22]. Additionally, researchers have made advancements in control charts to address situations with multivariate data exhibiting autocorrelation and time series effects [23-27]. Notably, Jarrett and Pan [28] proposed separate approaches for independent and autocorrelated processes. They introduced a dedicated multivariate autoregressive (MAR) control chart specifically designed for handling multivariate data with autocorrelation.

2.2 Residual control chart

2.2.1 T^2 Hotelling control chart

The T^2 Hotelling control chart, a more versatile version of the Shewhart chart, was introduced by Harold Hotelling in 1947 to handle multivariate observations. Unlike the Shewhart $\bar{X}$-chart which deals with single variables, the T^2 Hotelling chart can handle multiple variables simultaneously. It comes in two versions: for data grouped by subgroups and for individual observations. The Shewhart *X*-chart is basic tool for univariate control charts, where it measures process stability against significant changes. It assumes residuals (differences between observed values and expected values) have a zero mean and a standard deviation σ_r. An observation is considered in-control if its residual value falls within control limit defined by a factor λ. The T^2 Hotelling chart uses a different approach. It leverages the Mahalonobis distance [25] to compress residuals from multiple variables into a single value. An observation is considered in control if it satisfies a specific equation as the following Eq. (1). This equation considers factors like the number of observation (n); the number of variables (m); the residual vector of each observation (R_i); and a value from the Fisher distribution $F_{m;n-m;(\alpha)}$. The Fisher distribution is chosen based on a desired risk level (α), which helps determine the expected frequency of false alarms when in-control observations flagged as out-of-control. By analyzing the T^2 statistic value for each observation, the T^2 Hotelling control chart can effectively monitor processes with multiple interrelated variables.

$$T_i^2 = R_i^T \sum\nolimits_R^{-1} R_i \frac{m(n-1)}{n-m} F_{m;n-m;(\alpha)}; \quad \text{for } i = 1,2,\cdots,n \tag{1}$$

2.2.2 Multivariate CUSUM control chart

The CUSUM control chart was developed to overcome a weakness in Shewhart and T2 Hotelling charts. These traditional charts often miss gradual process changes because they only consider the most recent data point [9]. CUSUM charts address this by accumulating the deviations from a target value across residuals of past observations, making them more sensitive to subtle shifts. The most common CUSUM control method is Crosier's chart [29]. This method uses a statistical procedure defined by Eqs. (2) and (3). It starts with $S_0 = 0$, a matrix of zeros representing the initial state. Then, for each observation (i), it calculates a new S_i value based on the previous S_{i-1}, the current residual R_i, a reference value (k) and the estimated residual covariance matrix Σ_R^{-1}. The reference value (k) helps determine how quickly the CUSUM chart reacts to changes. Crosier's chart signals a potential process shift when a statistic called $T_S^2 = S_i^T \sum_R^{-1} S_i$, calculated using S_i and the inverse covariance matrix, exceeds a predefined limit (H). In simpler terms, the CUSUM scheme raises an alarm when the S statistic goes above a certain threshold (H), indicating a possible change in the process.

$$S_i = \begin{cases} 0 & \text{, if } C_i \le k \\ (S_{i-1} + R_i)\left(1 - \dfrac{k}{C_i}\right) & \text{, otherwise} \end{cases} \tag{2}$$

$$C_i = (S_{i-1} + R_i)\Sigma_R^{-1}(S_{i-1} + R_i)^T \tag{3}$$

Crosier's chart signal a shift when $T_S^2 = S_i^T \sum_R^{-1} S_i$ overcomes a predetermined limit H. Thus, if $S_i > H$, the chart indicates a process shift. To achieve the desired in-control run length (RL) characteristic, the parameters k and H must be determined beforehand. In CUSUM procedures, it is standard practice to assume a sample size of one. This simplification is widely adopted as it allows for the continuous monitoring of individual observations, facilitating the prompt detection of small shifts in the process. However, in some cases, it might be beneficial to consider larger sample sizes to account for variations and provide more robust detection capabilities, especially in processes where data is naturally grouped or collected in batches. Adapting the CUSUM procedure to accommodate different sample sizes can enhance its flexibility and effectiveness in various industrial and statistical applications. The multivariate CUSUM (MCUSUM) statistic S_i is designed to detect specific shifts in the process mean vector. This capability enables the identification of changes across multiple variables simultaneously, making MCUSUM particularly useful for monitoring complex processes where interactions between variables may signal deviations from the expected process behavior. By accumulating deviations from the target mean vector over time, the MCUSUM statistic provides a sensitive measure for detecting even small shifts, thus enhancing the ability to maintain quality control and process stability in multivariate settings. Additionally, the MCUSUM approach can be tailored to different types of shifts and can incorporate various weighting schemes to prioritize certain variables or shifts, further improving its applicability and effectiveness in diverse industrial and research environments:

$$S_i = max\{S_{i-1} + a^T R_i - k, 0\} \tag{4}$$

where,

$$a^T = \frac{\delta_r^T \Sigma_r^{-1}}{\sqrt{\delta_r^T \Sigma_r^{-1} \delta_r}}$$

The residual mean vector is denoted as δ_r, while Σ_r represents the variance-covariance matrix. In a MCUSUM scheme, any deviation from the target mean that exceeds k units is aggregated. In this context, k serves as the benchmark value for the scheme. The control scheme signals an out-of-control state when S_i surpasses a specified decision threshold, labeled as H [9].

2.2.3 Multivariate EWMA control chart

While CUSUM charts consider all past measurements equally, EWMA (Exponentially Weighted Moving Average) charts assign weights to recent observations based on their significance in depicting process behavior. A higher value of λ amplifies the impact of the most recent observation [5]. The iterative expression for EWMA statistics is described by Eq. (5),

$$Z_i = (1-\lambda)Z_{i-1} + \lambda R_i; \text{ for } i = 1,2,\cdots,n \tag{5}$$

where, λ is diagonal matrix of value $0 \le \lambda_j \le 1$, $j = 1,2,\cdots,m$. The multivariate EWMA (MEWMA) scheme signals if the

$$T_Z^2 = Z_i^T \sum\nolimits_Z^{-1} Z_i \tag{6}$$

surpasses a predetermined value H, where H>0 is chosen to achieve a specified in-control (on-target) ARL_0. The asymptotic form of the covariance matrix is $\Sigma_Z = \left(\frac{\lambda}{2-\lambda}\right)\Sigma_R$ [30].

Reynolds and Lu's study [31] explored the use of AR (1), AR (2), and ARMA (1, 1) models with residual *X*-charts. They identified a potential limitation: the residual *X*-chart might not be sensitive enough to detect certain types of process changes, specifically mean shifts. Those research, however, considered only for processes which has small order of p on autoregressive AR (p) model. Whereas real condition sometimes autocorrelation with high order (p>5) are occurred. Besides that, multivariable with high autocorrelation also must considered in one time. This condition usually occurs in the manufacturing industry with mass production and fast flow production. Therefore, the general multivariate autoregressive

(MAR) models should be developed to overcome multivariable and autocorrelation problem on statistical process monitoring using residual based multivariate control chart.

2.3 Applying ANN to SPM of multivariate auto-correlated observations

Artificial neural networks (ANNs) are increasingly used as powerful tools to estimate and forecast process outputs [32]. In particular, the multi-layer perceptron (MLP) is a versatile estimator, working for both classification and prediction tasks. For forecasting problems, a multilayer feed-forward ANN with a continuous output layer is ideal. When dealing with quality data exhibiting autocorrelation through an autoregressive model of order p (AR(p)), the average values for each time period depend on the averages of the previous p periods. Consequently, when using an ANN for forecasting, the input layer feeds the network with quality characteristic data from the past p periods. The output layer then predicts the quality characteristic vector for the target time period. During implementation, the network processes information from the previous p periods through the input layers to generate the forecast vector at the output layer. As highlighted by Arkat et al. [3], the residual vector for each period is simply the difference between the predicted and actual quality characteristic values.

Machine learning has seen growing adoption in statistical process monitoring (SPM) research over the past two decades. This trend reflects the potential of machine learning to detect and diagnose faults in industrial processes and production outcomes. ANNs, specifically, have been used for data analysis in SPM since the 1980s, as demonstrated by Arkat et al. [3]. Research has explored ANN applications in both univariate [33-35] and multivariate control charts [36-40]. Arkat et al. [3] proposed an ANN-based model for forecasting and building residual CUSUM charts for AR (1) multivariate processes. Additionally, Khediri et al. [5] explored using support vector regression to create control charts for monitoring more complex, non-linear, and autocorrelated multivariate processes.

2.4 Summary

Traditional methods often assume independence between observations, which is violated in continuous-flow manufacturing processes due to autocorrelation. This violation leads to increased false alarm rates and reduced average run length (ARL). While multivariate control charts address correlation among variables, they can be complex and computationally intensive, and they may not effectively identify specific variable contributions in out-of-control signals. Our proposed ANN-based model addresses these limitations by integrating a multivariate autoregressive (MAR) approach with neural networks, improving sensitivity to small shifts in the process mean vector and enhancing robustness to autocorrelation. The model offers better detection capabilities, reducing false alarms and improving ARL stability. Additionally, it provides detailed decomposition of out-of-control signals, allowing process engineers to pinpoint and address root causes of variations more effectively. These improvements enhance the reliability and practicality of SPM systems in modern manufacturing, leading to more timely and accurate quality control interventions, ultimately improving product quality and manufacturing efficiency.

In recent years, several studies have advanced the field of SPM, particularly in addressing the limitations of traditional control charts in handling autocorrelated and multivariate data. For instance, Wang and Asrini [41] proposed an enhanced EWMA control chart that incorporates machine learning techniques to better handle autocorrelated data, demonstrating improved sensitivity and reduced false alarm rates. Similarly, Yang and Sutrino [42] developed a hybrid SPM model that combines neural networks with traditional statistical methods to monitor complex manufacturing processes, showing significant improvements in detection capabilities and robustness to data variability.

With advancements in many automation processes, such as electronic component manufacturing, the assumption of independent distribution is frequently violated because the high frequency of sample selection results in observations that are closely related and dependent. It is crucial to understand how to apply and evaluate control charts designed to account for autocorrelation. Residual control charts offer valuable insights into device behavior over time and have effective detection capabilities. However, they do not entirely address the needs for handling autocorrelation and multiple variable observations.

3. METHOD

This study aims to present a residual control chart using MAR model with ANN (MAR-ANN) to solve the SPM problem related to multivariate with auto-correlated observations. Moreover, this study makes diagnostic of out-of-control signal in multivariate control chart using decomposition technique. Comparison of multivariate control chart with univariate one is also conducted. Figure 1 shows the operational procedure of the proposed mothed. Multiple variables are defined as the quality parameter which correlate to each other, and each variable is of time series.

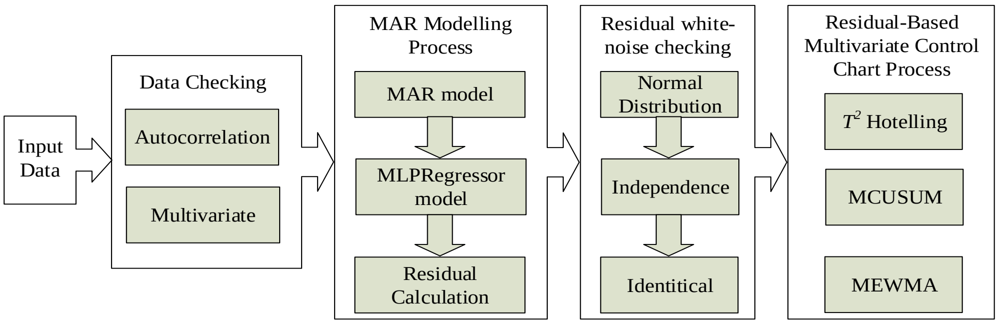


Figure 1. Procedure to build the proposed control chart

Correlation test is employed to know the strength of correlation between variables. In this study, correlation test determines the correlation between quality parameters of a product. If there is a correlation between quality parameters, then the control chart preparation is based on a multivariate control chart approach because it will involve more than one quality parameter in one chart. The hypothesis used in testing the correlation between quality parameters is as follows. To determine whether there is a correlation between quality parameters is based on the p-value.

H_0: $\rho = 0$ or there is no correlation
H_1: $\rho \neq 0$ or there is a correlation

This study tackles autocorrelation in process data using a method developed by Loredo et al. [6]. This method prioritizes residual-based control charts, which have proven more effective than traditional charts in detecting mean shifts when dealing with short-run, autocorrelated data. To identify variables potentially affected by autocorrelation, the study performs an autocorrelation test on each variable. These tests assess whether a variable exhibits a relationship with its own past values over time. A helpful tool for visualizing autocorrelation is the autocorrelation function (ACF) plot. If a variable's ACF plot shows a significant lag, it suggests the presence of autocorrelation. To address autocorrelation, the study employs time series modeling. This modeling process ensures the model's errors (residuals) meet the assumption of white noise, meaning they are uncorrelated with each other. The autocorrelation coefficient, calculated at a specific time lag (k), measures the correlation between a variable's value at a given time (t) and its value k periods earlier (t-k). Essentially, it indicates how closely the variable's past values influence its current value. If the autocorrelation plot dips below the 95% confidence interval at a particular lag, it signifies the presence of significant autocorrelation at that time lag.

Figure 1 presents a four-step procedure. First, data are checked for each variable by ACF and correlation between variables by Pearson's correlation. Second, MAR modelling process determines the model considering autocorrelation and multivariate. To estimate MAR, this research proposes an ANN with MLPRegressor approach. Third, residual white-noise checking is conducted to ensure all residual variables can be used for the multivariate control chart. White noise residual checking involves multivariate normality, independence and identical test. Then, fourth step builds a residual-based multivariate control chart where residual is the difference between actual value and estimated value based on the MAR model of each variable.

If the quality characteristics of an autocorrelated process follow an AR (p) model, the mean vector for each period depends on the mean vectors from the previous p periods. In such cases, the inputs for the desired artificial neural network (ANN) consist of the quality characteristic vectors from the previous p periods, while the output represents the quality characteristic vector to be forecasted for the next period. Before constructing the ANN, the multivariate autoregressive (MAR) model is typically applied to determine the autoregressive order p for each factor in the time series. This helps in understanding the dependencies and lagged effects among the quality characteristics over time, ensuring that the ANN model captures the relevant temporal relationships effectively.

This study, following the work of Khediri et al. [5], utilizes time series estimation for a multivariate process using a multivariate autoregressive (MAR) model. The MAR model considers the influence of past values on each variable in the process. Suppose a process with m variables where each variable Y_i for i ranges from 1 to m at specific time t denoted as Y_{it}. The MAR model considers the values of all m variables at p previous time steps to influence the current value (t) of variable Y_i. In other words, Y_{it} is determined by the values of Y_j at times (t-1), (t-2), ..., (t-p) for all j variables (from 1 to m). Eq. (7) summarizes this concept mathematically. It represents Y_{it} as a function of the lagged values of all m variables. The MAR model then estimates this function, denoted by $\hat{f}$, allowing to predict future values (Y_{it}) for each variable using Eq. (8). Eq. (8) essentially replaces the unknown function f with its estimated version ($\hat{f}$) to predict Y_i at time t.

$$Y_{(i=1,2,\ldots,m)t} = f(Y_{1(t-1)},\cdots,Y_{1(t-p)},\cdots,Y_{m(t-1)},\cdots,Y_{m(t-p)}) \qquad (7)$$

$$\hat{Y}_{(i=1,2,\ldots,m)t} = \hat{f}(Y_{1(t-1)},\cdots,Y_{1(t-p)},\cdots,Y_{m(t-1)},\cdots,Y_{m(t-p)}) \qquad (8)$$

If the estimation is accurately performed, the error term vector is calculated based on Eq. (9). This vector will be used to generate the control chart, which will be time-independent and typically distributed with a mean of zero.

$$\widehat{e_t} = Y_{(i=1,2,\cdots,m)t} - \hat{Y}_{(i=1,2,\cdots,m)t} \qquad (9)$$

If a shift occurs in the process, it will no longer be accurately described by the function f, and consequently, the estimated residual term $\widehat{e_t}$ will also be affected and shifted. To determine the residual used for the control chart, this study employs the multivariate autoregressive (MAR) model, as specified in Eq. (10).

$$y_t = c + \emptyset(B)y_t + e_t \qquad (10)$$

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + e_t \qquad (11)$$

where,
$y_t = (y_{1,t}, y_{2,t}, \ldots, y_{m,t})'$ is (mx1) vector of variable Y
$c = (c_1, c_2, \ldots, c_m)'$ is (mx1) vector of constant value
$e_t = (e_{1,t}, e_{2,t}, \ldots, e_{m,t})'$ is (mx1) vector residual, with assumption $e_t \sim$IIDN $(0, \Omega)$ and $var(e_t e_t)$=Ω.
$\emptyset$ =coefficient of MAR model, matrix (mxm)
t=1, 2, …, n
B=backshift operator
m=number of variables
p=order of MAR

In this study, the MAR residual control chart, which involves a number of input and output variables and a fitting technique to find the satisfied residual, is empowered by a multilayer perceptron regressor (MLPRegressor) (Alpaydin, 2010) to obtain good fitting result. MLPRegressor can approximate the nonlinear functions of the input for regression by forming higher-order representations of the input features using intermediate hidden layer.

4. EXPERIMENT RESULT AND DISCUSSIONS

4.1 Manufacturing process

This study applies the MAR-ANN model to electronics product manufacturing processes, encompassing stages like stamping, electroplating, injection molding, assembly, and packaging (depicted in Figure 2). These processes operate on a high-speed continuous production line characterized by multivariate and autocorrelated properties. An automatic optical inspection (AOI) system is integral to the process, facilitating data collection. High-precision instruments, regularly calibrated for accuracy, including digital calipers, micrometers, and AOI systems, are utilized to measure product dimensions and features. Specifically, AOI systems record product feature measurements. The MAR-ANN model proposed in this study aims to enhance defect detection capabilities, leveraging the structured data from AOI and other instruments to improve quality monitoring throughout the manufacturing stages.

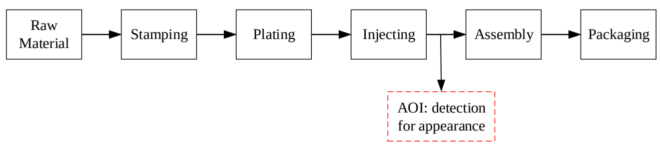


Figure 2. Manufacturing process of the product under investigation

Table 1. Product feature and variable notation

Feature	Variable Notation
Excess metal material is present at the terminal.	Y1_1
Excess colloids appear in the hold-down of the metal.	Y1_2
Excess metal material is found on the plastic body.	Y2_1
Excess plastic material is present on the product's edge.	Y2_2
Overflow occurs on both sides.	Y3
The root is overflowed.	Y4

In this study, the automatic optical inspection (AOI) system detects key defect types such as "overflowed", "extra-materials", and "metal debris". These defects are identified based on numerical specifications such as length, width, and area measured by the AOI system. Each product is characterized by six features, as detailed in Table 1, which describes each variable. The data collection process involves measuring products in batches, with each batch comprising 100 units. For the MAR-ANN control chart analysis, this study collects samples from 300 such batches. This structured approach ensures that a comprehensive dataset is used to develop and validate the MAR-ANN model for effective quality control in the manufacturing process.

4.2 Residual-based multivariate control by MAR-ANN model

The proposed MAR-ANN model is implemented according to Figure 1.

4.2.1 Data checking

The MAR (multivariate autoregressive) model assumes that each time series in the system influences others, allowing predictions based on past values of all series involved. Granger's causality test is a method used to assess these dependency relationships by testing whether past values of one series help predict another. In the study, Table 2 presents the results of Granger's causality test for all possible combinations of time series in a given dataset, storing the corresponding p-values in an output matrix. A p-value less than the 5% significance level indicates a significant causal relationship, where the series in the column influences the series in the row. For example, a p-value of 0.0000 in (row 1, column 2) suggests that Y1_2 (column) causes Y1_1 (row). Conversely, a p-value of 0.000 in (row 2, column 1) indicates that Y1_2 (row) causes Y1_1 (column). Therefore, Table 2 demonstrates that there are significant correlations among the variables overall. Specifically, it can be concluded that variables Y1_1 and Y1_2; Y1_1 and Y2_2; Y1_1 and Y3; Y2_1 and Y2_2; Y2_1 and Y4; Y2_2 and Y3 are correlated based on the p-values obtained from Granger's causality test. These findings help validate the interconnectedness assumed by the MAR model in your analysis.

ACF test of each variable is shown in Figure 3, showing that almost all variables have lags over than the red likelihood limit (95%), which means every variable has significant autocorrelation. Vector autoregressive model found that the optimal lag to define order p is 16 (p=16). This order was chosen based on the minimum Akaike Information Criterion (AIC) value.

4.2.2 MAR modeling process-constructing residuals control chart using ANN model

This approach tackles the challenges of analyzing complex, autocorrelated, and multidimensional quality data by combining a MAR model with an ANN. The MAR model excels at capturing the data's temporal nature and the interconnectedness between variables. The ANN, on the other hand, is adept at learning non-linear relationships and becoming more sensitive to subtle changes in the average values of the entire quality measurement process. To train and validate the effectiveness of this MAR-ANN model, we utilized a dataset gathered from a continuous-flow electronic product manufacturing line. The data was meticulously divided into training (70%), validation (15%), and testing (15%) sets. This methodical split ensures the model's robustness and generalizability. The training set serves as the foundation for model fitting, while the validation set allows for fine-tuning crucial hyperparameters that influence the ANN's performance. Finally, the test set provides an unbiased assessment of the model's overall accuracy. Selecting the optimal hyperparameters is paramount for maximizing the ANN's effectiveness. We employed a grid search technique to identify the ideal configuration, encompassing factors like the number of hidden layers, the number of neurons within each layer, the learning rate, and parameters for controlling overfitting. This grid search was meticulously conducted using cross-validation on the training data. Ultimately, the combination of hyperparameters that yielded the best performance on the validation set was chosen for the final model.

Eq. (12) represents an autoregressive process with 6 variables and order p=16.

$$Y_{(i=1,2,\ldots,6)t} = f\,(Y_{1(t-1)},\cdots,Y_{1(t-16)},\cdots,Y_{6(t-1)},\cdots,Y_{6(t-16)}) \quad (12)$$

Estimation of the process using ANN provides $\hat{f}$ which allows to predict $Y_{(i=1,2,\ldots,m)t}$ as Eq. (13).

$$\hat{Y}_{(i=1,2,\ldots,6)t} = \hat{f}\,(Y_{1(t-1)},\cdots,Y_{1(t-16)},\cdots,Y_{6(t-1)},\cdots,Y_{6(t-16)}) \quad (13)$$

Table 2. Pearson's correlation test between variables

	Y1_1_x	Y1_2_x	Y2_1_x	Y2_2_x	Y3_x	Y4_x
Y1_1_y	1	**0.000***	**0.003***	0.170	**0.003***	0.071
Y1_2_y	**0.000***	1	**0.000***	0.155	0.813	**0.000***
Y2_1_y	0.145	**0.000***	1	**0.027***	0.101	**0.000***
Y2_2_y	**0.000***	0.2957	0.282	1	**0.000***	**0.027***
Y3_y	**0.031***	0.7830	0.094	**0.000***	1	0.281
Y4_y	0.085	**0.000***	0.381	0.101	0.115	1

Note: (*) at 5% significance level

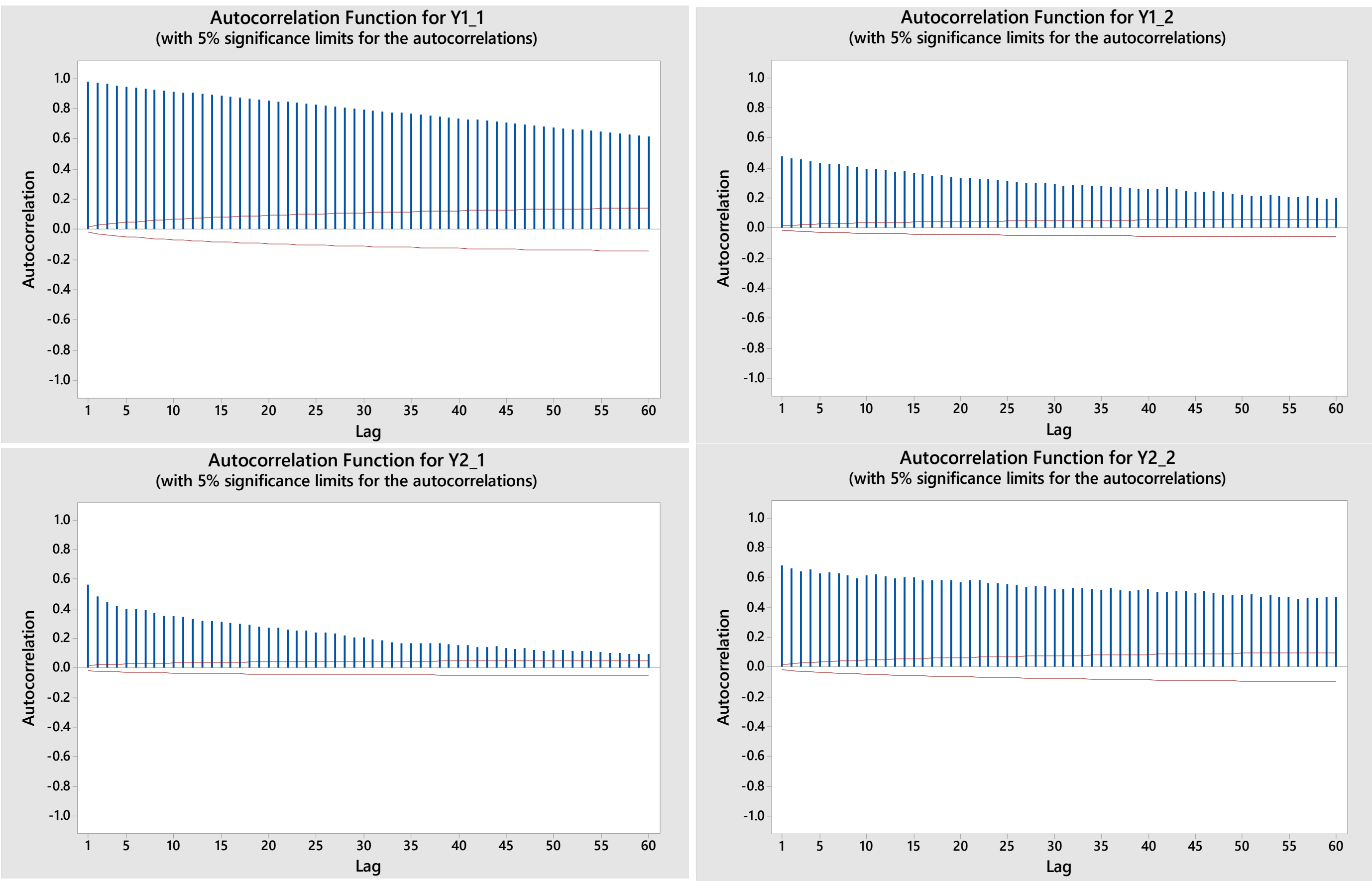
The specific ANN model that used to figure out the autoregressive model with 6 variables and order p=16 in this case is MLPRegressor. The model, trained on 14,000 observations from an electronic product manufacturing process, includes a single hidden layer with 50 neurons and uses the 'relu' activation function. Key hyperparameters include an alpha of 0.0001 for regularization, a learning rate of 0.001, and the Adam optimizer. The model underwent up to 1000 iterations, with early stopping disabled, and employed cross-validation (70% training, 15% validation, 15% test split). These details ensure the model's reproducibility and highlight the robustness and appropriateness of our approach. Using the MLPRegressor which involved multiple outputs, the selected optimal model that used in this study is shown as following code:

```
# Simple MLPRegressor with ReLU activation and Adam optimizer
regressor = MLPRegressor(
    activation='relu'; # Non-linear activation
    solver='adam',# Efficient optimizer
    hidden_layer_sizes=(50,);# Single hidden layer with 50 neurons
    learning_rate_init=0.001; # Initial learning rate
    max_iter=1000#Maximum training iterations)
```

The R-square value of 91.4% indicates that the MLPRegressor model explains a substantial portion, 91.4%, of the variance in the data, highlighting a strong fit for the MAR-ANN model to the observed values. To verify the white noise assumption of the residuals, the residuals are computed by subtracting the predicted values from the actual observations for each Y variable. Subsequent checks include ensuring the residuals have a mean close to zero, exhibit no significant autocorrelation through plots or tests like the Durbin-Watson test, and demonstrate constant variance (homoscedasticity) across different values. Meeting these criteria indicates that any remaining patterns in the data are likely due to random noise, validating the accuracy and reliability of the model's predictions.

Moreover, in terms of white noise checking, residuals should follow multivariate normal distributions with mean of zero and variance equal to one, and the residuals are free of auto-correlation effects. The following step is a checking of white noise assumptions of residuals. Firstly, multivariate normal distribution checking in this study is done by the Henze-Zirkler test [43]. According to this test, we found that the p-value is equal to 0.150, which means all of residual variables have already followed multivariate normal distributions with significance value at 5%.

Next, independence assumption checking for residuals is conducted by ACF, as shown in Figure 4. The lags of residual variables Y1_1; Y1_2; Y3 and Y4 are lower than the red likelihood limit (95%) and the autocorrelation value is around zero. Meanwhile, the lags are over than the red likelihood limit (95%) and the autocorrelation value is lower than 0.4 for residual variables Y2_1 and Y2_2, which means the correlation is weak so the effect can be ignored. Therefore, it can be concluded that all residual variables are free of the autocorrelation effect. Therefore, those residual variables can be used to create multivariate control chart.



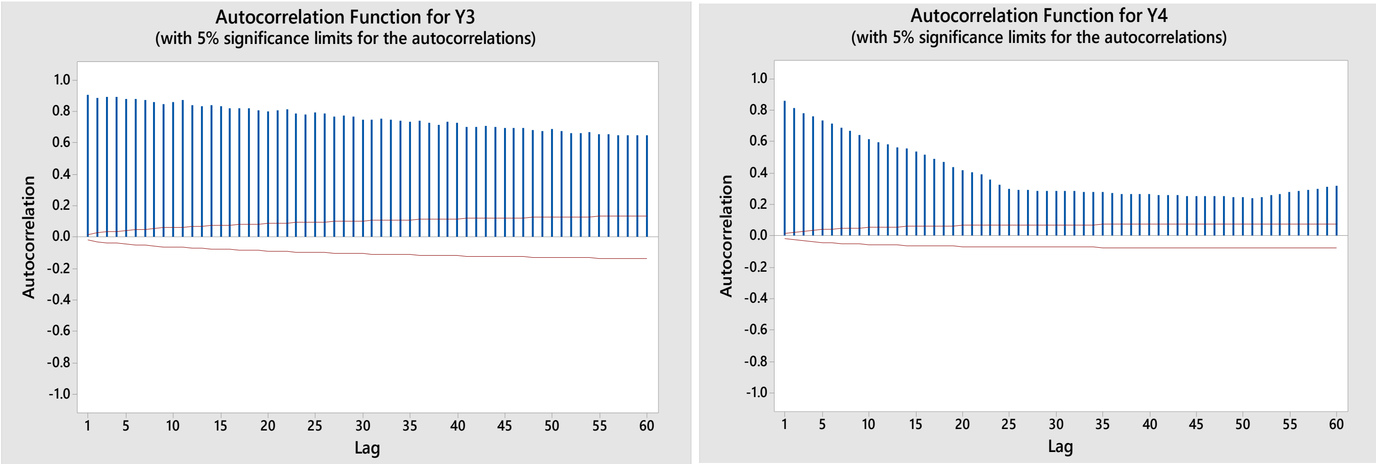


Figure 3. Autocorrelation test of each variable

Table 3. Descriptive of residual model of each variable

Residual of Variable	Mean	Variance
Y1_1	-0.001	0.0234
Y1_2	0.081	0.3685
Y2_1	-0.037	0.2193
Y2_2	0.024	0.148
Y3	-0.002	0.0004
Y4	0.052	0.627

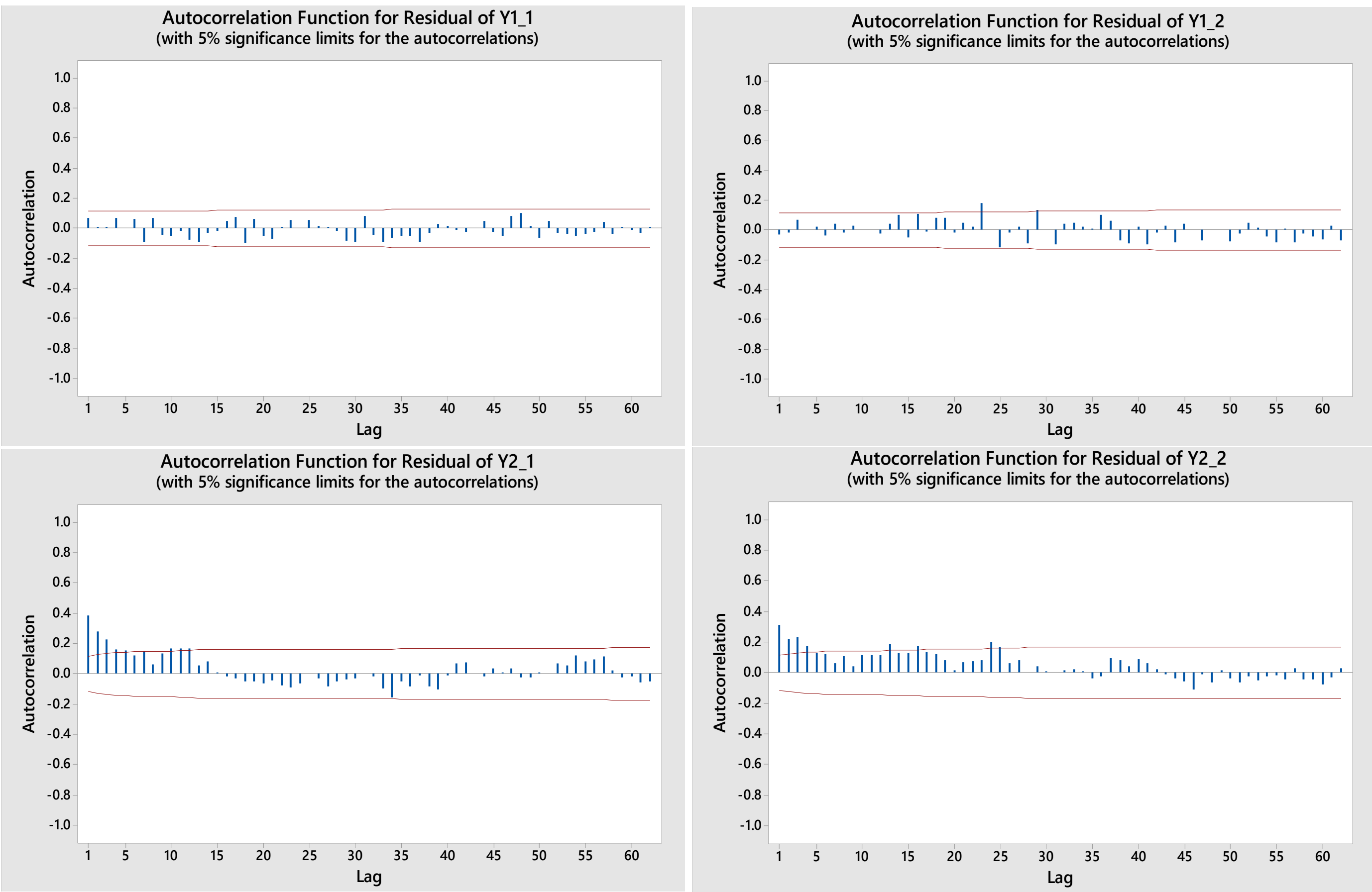
Third step is residual white noise checking. Table 3 shows that the mean and variance of each residual variable almost near zero. Therefore, all residual variables have already satisfied the white noise assumption. The application of residual data satisfied the assumption of normality distribution and absence of autocorrelation effects.

All quality characteristics are monitored simultaneously. Table 4 illustrates the correlation among the six residual variables.

Multivariate T^2 Hotelling control chart

Multivariate T^2 Hotelling control chart is constructed. Multivariate T^2 Hotelling control chart for original data with upper control limit (UCL) value equal to 29.2 is illustrates in Figure 5(a) showing that there were 50 instances where the mechanism failed, which shown by some points are out of control. There are oscillating and it fails out at points particularly after sample 157th. This behavior comes from the dependence of measurements over the time on original data.

Instead, by using residual data, the number out-of-control samples decreases down to 9 samples. Multivariate T^2 Hoteling control chart using residual data is more stable than multivariate T^2 Hotelling control chart using original data, as shown in Figure 5(b).



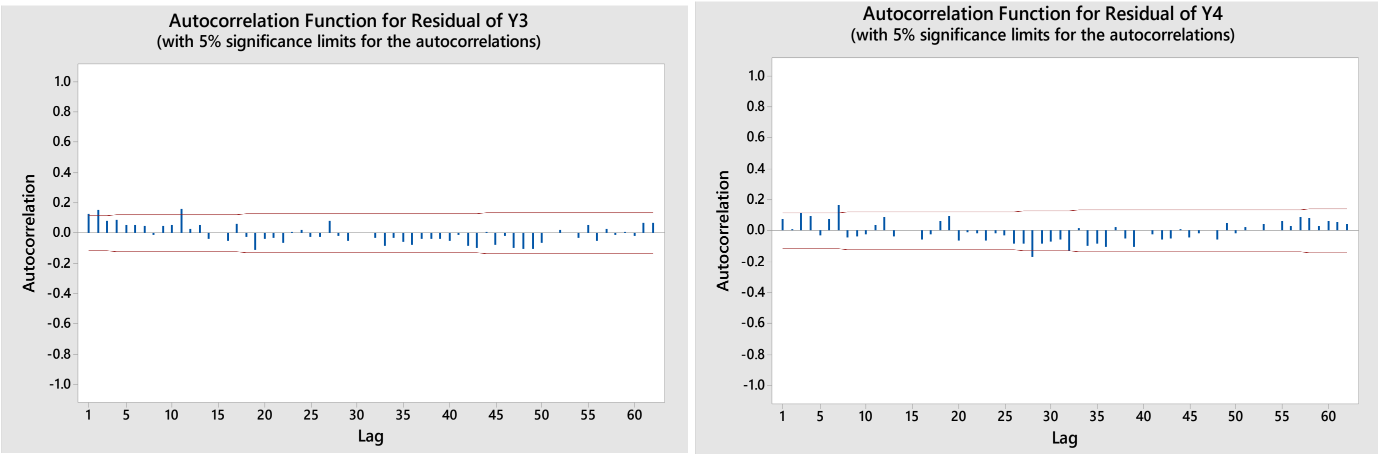
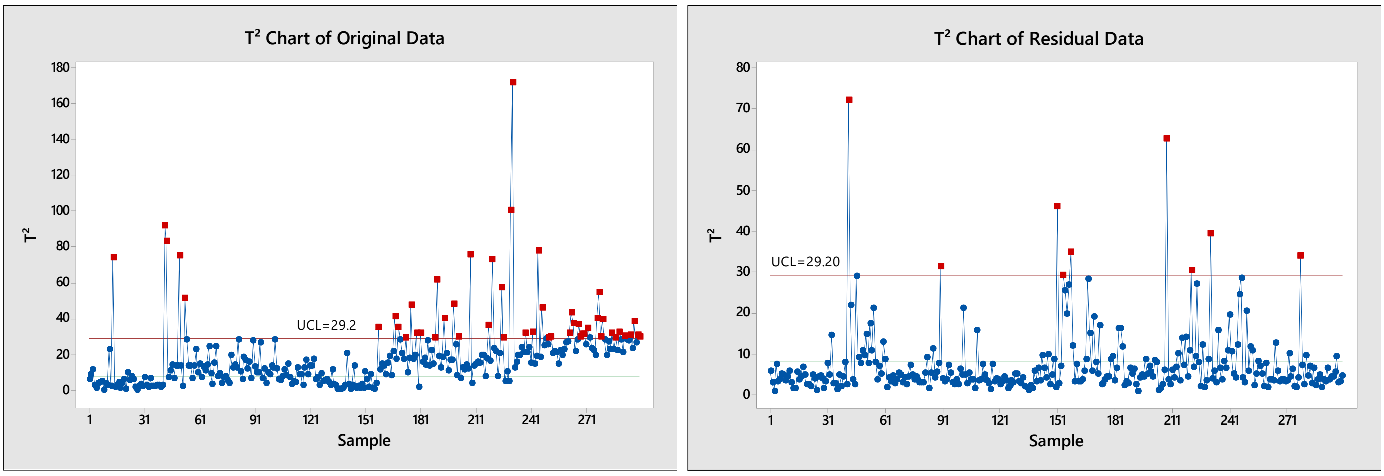


Figure 4. Autocorrelation test of each residual variable

Table 4. Correlation test between residual variables

Characteristics	Variables	Residual of Y1_1	Residual of Y1_2	Residual of Y2_1	Residual of Y2_2	Residual of Y3
Residual of Y1_2	Correlation	0.046				
	P-Value	0.431				
Residual of Y2_1	Correlation	-0.092	0.064			
	P-Value	0.111	0.266			
Residual of Y2_2	Correlation	0.105	0.112	-0.019		
	P-Value	0.069	0.052	0.743		
Residual of Y3	Correlation	0.189	0.087	0.035	0.064	
	P-Value	**0.001***	0.133	0.542	0.268	
Residual of Y4	Correlation	0.272	0.033	0.131	-0.014	0.144
	P-Value	**0.000***	0.571	**0.023***	0.808	**0.013***

Note: (*) at 5% significance level



(a) by original data

(b) by residual data

Figure 5. T^2-Hotteling multivariate control chart

Table 5. Decomposed T^2 Hotteling value

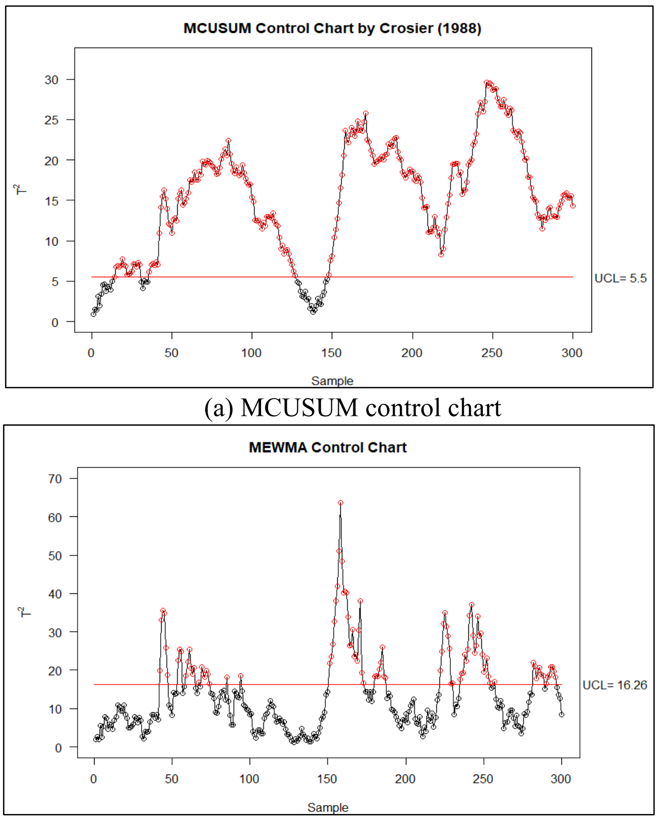
Sample	Variables					
	Y1_1	Y1_2	Y2_1	Y2_2	Y3	Y4
42	11.44	0.922	3.919	0.756	41.316	3.766
90	14.47	0.187	0.007	4.659	0.518	4.742
151	0.033	0.726	0.312	0.115	1.314	39.02
154	10.73	0.390	15.44	2.142	0.145	0.559
158	1.450	0.622	7.821	0.239	0.044	19.47
208	5.918	8.376	0.967	40.04	1.127	1.883
221	0.066	0.101	4.608	26.74	1.552	0.113
231	3.693	24.50	0.721	2.862	7.022	0.302
278	21.09	1.052	0.119	0.005	2.198	3.815

Decomposition is a valuable diagnostic technique for identifying out-of-control signals in multivariate control charts, particularly in T^2 Hotelling charts. It breaks down the T^2 statistic into components that represent the contribution of each individual variable to the out-of-control signal. This approach involves estimating values d_i for each variable and focusing on those variables where d_i) values are relatively large. Table 5 typically displays the variables with the highest d_i values, indicating which variables contribute most significantly to the out-of-control signals detected in the multivariate T^2 Hotelling control chart. This helps pinpoint specific factors or characteristics that may need attention or correction in the manufacturing or process control environment. Y1_2, Y2_1, and Y3 are responsible for out-of-control signals on sample 231st, 154th, and 42nd, respectively. Y1_1 is responsible for samples 90th and 278th. Y2_2 is responsible for samples 208th and 221st. Y4 is responsible for samples 151st and 158th.

MCUSUM and MEWMA control chart

The study utilized RStudio (version 2020) and the MSQC package to create MCUSUM and MEWMA control charts. These charts were designed to identify subtle changes in the process by setting a specific false alarm rate (chosen to be 5%). The configuration also included a reference value (k=0.5) and a decision limit (h=5.5). The MCUSUM chart, analyzing the data's residuals, proved to be significantly more adept at detecting small shifts in the overall process mean compared to the standard T^2 Hotelling chart. This improved sensitivity is evident in Figure 6(a), where the MCUSUM chart detects the first process change much earlier (sample 14) compared to the T^2 chart (which only signals at sample 42) under identical test conditions (number of variables: p=6, subgroup size: n=1, and desired false alarm rate: ARL_0=200).

Conversely, Figure 6(b) illustrates that the MEWMA control chart exhibits comparable sensitivity to the multivariate T^2 Hotelling control chart in detecting process changes. This comparison highlights the effectiveness of MCUSUM and MEWMA charts in differentiating their capabilities in sensitivity relative to traditional T^2 Hotelling control charts in process monitoring and quality control scenarios.



(a) MCUSUM control chart

(b) MEWMA control chart

Figure 6. Multivariate control charts using residuals data

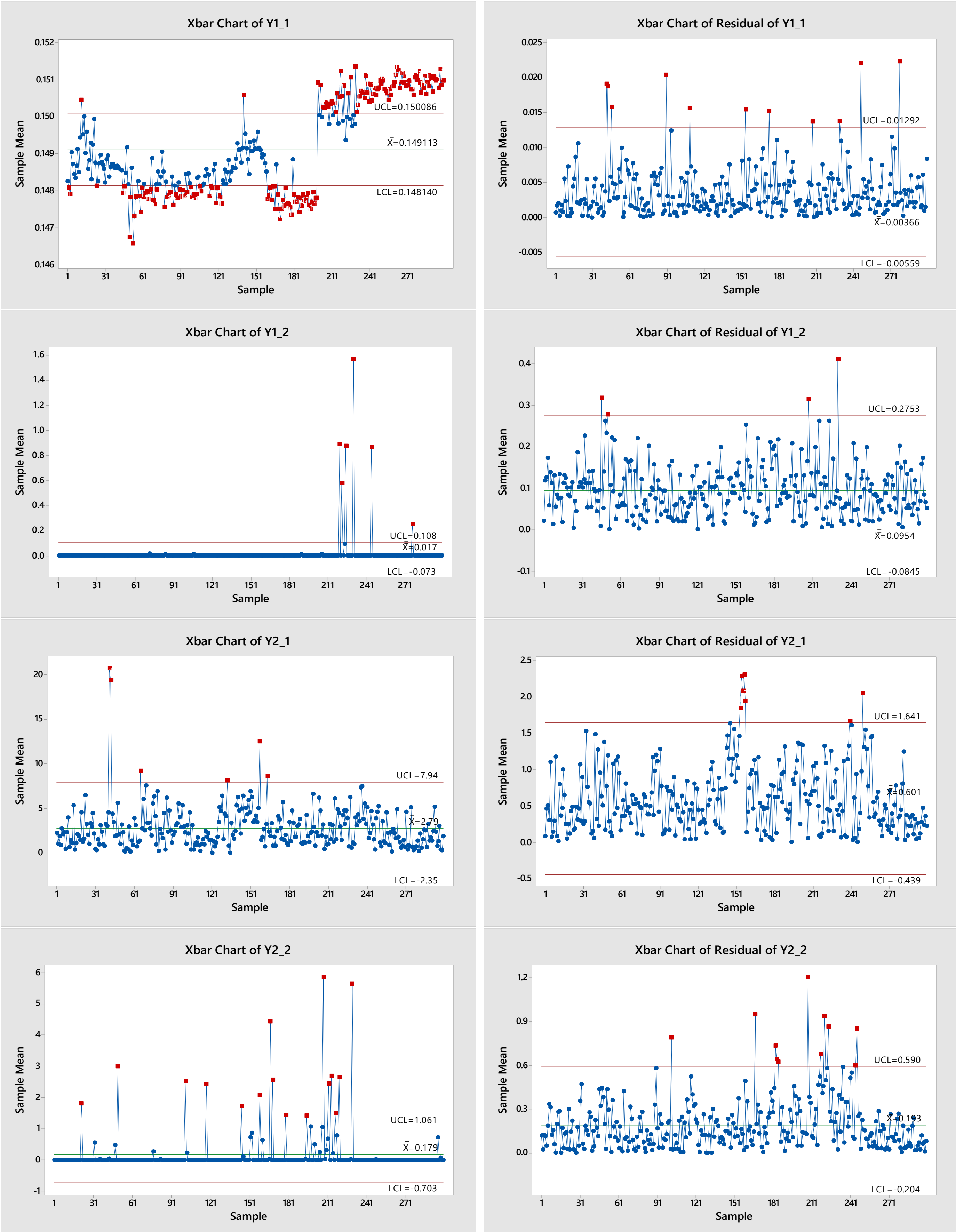
Implementing T^2 Hotteling control chart, MCUSUM chart and MEWMA chart for the obtained residual data can overcome multivariate autocorrelated data effectively. When compared with MCUSUM and MEWMA, T^2 Hotteling has better performance in detecting small shifts in the process. Meanwhile, the MCUSUM residual chart and the MEWMA residual chart show a large shift from the average. In addition, T^2 Hotteling also shows stable shifts around the average. However, the MCUSUM chart and the MEWMA chart show oscillations in shifts and even show a trend. This shows that the T^2 Hotteling residual chart has better performance than the MCUSUM and MEWMA residual control charts.

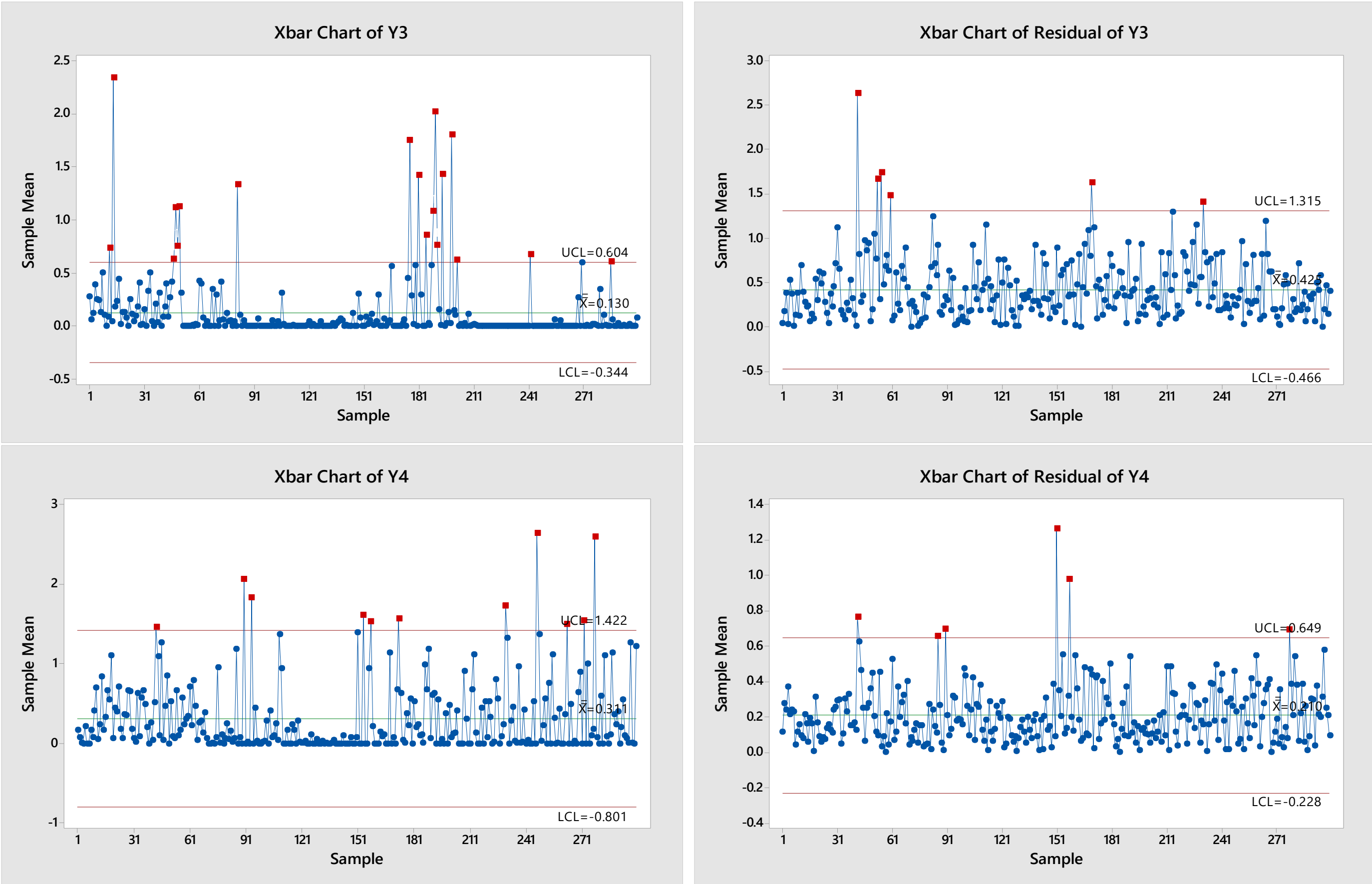
4.3 Comparison univariate control chart between original and residual data

In this section, Figure 7 presents a comparison between univariate control charts based on original data and residual data. The findings illustrate that the residual control chart outperforms the original data-based chart, particularly when the original data exhibit significant time series effects indicated by high autocorrelation. Specifically, Figure 7 demonstrates that control charts based on the original data exhibit more instances of out-of-control signals compared to those based on residual data. This indicates that using residuals, which account for the modeled effects and reduce autocorrelation, leads to improved performance in detecting deviations from the expected process behavior. Thus, employing residual-based control charts can enhance the accuracy and reliability of quality control measures in manufacturing or other monitored processes. Using three times of standard deviation from the center line rules, based on original data control chart, there are 181 samples, 6 samples, 6 samples, 16 samples, 18 samples, and 11 samples are out-of-control for each variable Y1_1, Y1_2, Y2_1, Y2_2, Y3 and Y4; respectively. Otherwise, using the same rules for testing, based on the residual data control chart, number of samples out of control decreasing into 11 samples, 4 samples, 7 samples, 11 samples, 6 samples and 6 samples for each variable Y1_1, Y1_2, Y2_1, Y2_2, Y3 and Y4; respectively. Even though variable Y2_1 has increasing number of samples out of control in residual data control chat, but there five consecutive points of out-of-control samples are getting large shift from the centerline.

The overall impression of process stability shown by control charts using residual data are rather different than was obtained from the control charts based on the original data. Otherwise, univariate control chart by original data for each variable, the pattern also shows the trend and large shift from the average. It might cause by the autocorrelation effects that happened on original data. As shown by the Figure 3, we see that the autocorrelation effect of the original data is very high which shown by the significant lag.

To address the practical implications of our proposed model in a real-world manufacturing context, we emphasize several key benefits. Firstly, the MAR-ANN model enhances detection sensitivity, enabling the early identification of potential quality issues. This allows for prompt corrective actions, reducing the incidence of defective products and minimizing rework, ultimately enhancing overall product quality. Additionally, the model effectively handles autocorrelation, a common challenge in traditional control charts, ensuring more reliable monitoring and reducing false alarms. This reliability is crucial for maintaining consistent product quality in continuous-flow manufacturing processes. Furthermore, our model is scalable and adaptable to various manufacturing processes with complex, multivariate, and autocorrelated data, making it suitable for diverse industries, from electronics to automotive. The implementation can be seamlessly integrated with existing manufacturing execution systems (MES) and statistical process control (SPC) software, allowing manufacturers to leverage advanced analytics without overhauling their current systems. This integration, coupled with the model's ability to lower operational costs by improving detection of process deviations and reducing false alarms, highlights its economic impact. Additionally, successful implementation requires comprehensive training for operators and engineers, demonstrating the model's benefits in improving process control and reducing false alarms. By promoting a culture of continuous improvement, manufacturers can use insights gained from the model to refine their processes continuously and maintain a competitive edge.





(a) (b)

Figure 7. Univariate control chart: (a) $\bar{x}$ control chart of original data; (b) $\bar{x}$ control chart of residual data

5. CONCLUSION

This case study highlights the importance of checking for autocorrelation and analyzing time series data before using control charts. Autocorrelation, where observations are dependent on previous ones, can negatively impact control chart performance. It can lead to more false alarms, as seen in charts built with raw data. Furthermore, in multivariate control charts, autocorrelation can mask the true relationships between variables. Additionally, dependence between variables can affect the performance of even univariate control charts. Therefore, using multivariate control charts is generally recommended.

To address the issue of autocorrelation in multivariate data, the paper suggests employing a combined approach: an ANN-based MAR (multivariate autoregressive) model. This approach aims to mitigate the effects of autocorrelation and improve the effectiveness of control charts. While univariate control charts are simpler to implement, they can be misleading when dealing with correlated variables. In such cases, the T^2 Hotelling control chart with decomposition techniques is a better option. This method helps identify which specific variables are contributing to out-of-control signals. The residual control charts, derived from the ANN-based model, perform significantly better in detecting mean shifts. This improvement is particularly evident in terms of sensitivity, where residual control charts showed a higher capability in identifying small process changes compared to traditional control charts. By emphasizing the practical benefits of residual control charts in handling autocorrelated multivariate data, our study contributes to the field by showcasing an effective solution for improved process monitoring and quality control. This approach offers valuable insights and practical implications for practitioners aiming to enhance their process control systems.

Based on the analysis of the case study, it is evident that in scenarios where detecting small changes in process parameters is critical, MCUSUM and MEWMA charts offer advantages over the T^2 Hotelling control chart. These alternative control charts exhibit superior run length performance and greater sensitivity in detecting minor shifts in the process's mean vector. This heightened sensitivity enables quicker response and action in maintaining process quality and efficiency. Given that the data in this study were derived from product specifications measured by an AOI system, which operates on numerical values, an intriguing area for future research involves exploring the application of P control charts. P control charts are pertinent for monitoring defect proportions and could provide valuable insights when applied to control charts using image data as input. Analyzing and interpreting control charts with image data presents a promising avenue to enhance quality control methodologies, particularly in sectors reliant on visual inspection and image-based measurements. This potential research direction could further advance understanding and implementation of robust quality control strategies in manufacturing and related industries.

In future studies, we aim to investigate the optimal selection and sensitivity of ANN models for handling multivariate time series data in industrial processes. This will involve conducting comprehensive experiments to compare various

ANN architectures (e.g., MLP, RNN, LSTM, GRU) and configurations (e.g., number of layers, neurons per layer, activation functions) to identify the most suitable models. Additionally, we will perform a sensitivity analysis by systematically varying key ANN parameters such as learning rate, hidden layer sizes, and regularization terms, as well as introducing variations in data quality like noise and missing data. By evaluating the impact of these changes on performance metrics, we intend to determine the robustness and stability of the ANN models and identify the configurations that produce the most representative and reliable residuals for process monitoring. This research will provide deeper insights into optimizing ANN models, enhancing the effectiveness of residual control charts, and offering valuable guidance for practitioners and researchers in improving industrial process monitoring and quality control.

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