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Research Article

THE UTILISATION OF SPECIAL CAUSE CONTROL CHARTS IN THE PRESENCE OF AUTOCORRELATED DATA

Sermin ELEVLİ*[1]

[1]*Ondokuz Mayıs University, Dept. of Industrial Engineering, SAMSUN;* ORCID: 0000-0002-7712-5536

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ABSTRACT

The basic assumption of traditional quality control charts is that data taken from the process are independent and identically distributed. However, the independence assumption is often not valid in practice as autocorrelation amongst the data becomes an inherent characteristic in many processes. Since any false judgment about process stability causes unnecessary interventions to process, it is important to investigate the independence assumption firstly and then to use the suitable control chart type. If autocorrelation is recognized in data, appropriate time series model can be used to model the correlative structure and then control charts can be applied to the independent and identically distributed stream of the residuals. This kind of control charts are called as Special Cause Control (SCC) Charts. In this study, SCC chart was compared with the outcomes of Individuals Control (IC) Chart. In the presence of autocorrelation, while IC chart gave a lot of false signals of special cause variation, SCC chart gave three signals of special cause variation.
Keywords: Autocorrelation, process control, quality control charts.

1. INTRODUCTION

Since variation is a fact of nature and industrial life, the variability of a process is inevitable. There are two types of process variation: 1) Random process variation (common cause variation) is the natural variation in a process, 2) Special cause variation (assignable cause variation) caused by unusual occurrences. A process is in statistical control when common causes are the only source of variation. Presence of assignable variation is an indicator of out-of-control situation. Because of this, it is important to identify and try to eliminate assignable-cause variation. Control chart is an effective tool of statistical process control to detect assignable causes of variation in a process.

A control chart is basically a time series graph with control limits. In order to detecting shifts or trends, a center line is added as a reference. Upper and lower control limits (UCL and LCL) are computed from available data and drawn equal distance from the center line. A stable and consistent pattern of variation over time is a characteristics of statistical control. Uncontrolled variation associated with assignable causes is characterized by huge variation over time.

A standard assumption of traditional control charts is that observations of the process are independently distributed with constant mean and variance. Autocorrelation is defined as the

* Corresponding Author: e-mail: sermin.elevli@omu.edu.tr, tel: (362) 312 19 19 / 7603

degree of correlation between the values of a given time series. The existence of autocorrelation in data causes a h igh probability of wrong alarms resulting from detecting “assignable causes” that do not exist and not detecting “assignable causes” that truly exist (Table 1).

Table 1. Errors of Process Control

	Alarm	No Alarm
In Control	Type I Error	No Error
Out of Control	No Error	Type II Error

The effect of autocorrelation on control charts has been studied by many researchers such as Wardell et al. (1992), Young and Winistorfer (2001), Elevli et al. (2009), Noskievicova (2009), Karaoglan and Bayhan (2011), Russo et al. (2012), Wang et al. (2013), Kandananond (2014), Perzyk and Rodziewicz (2015), Ma et al. (2018). In all these studies, it is found that autocorrelation results in an increase in the number of assignable cause variation signals on control chart. False signals lead to an unnecessary adjustment of process that is in statistical control (Type I Error).

If significant autocorrelation in the observations is present, it is necessary to modify traditional methodology to account for this autocorrelation. The approach that has been proven useful in dealing with time-dependent data consists of the following steps: 1) directly modelling the correlative structure with Autoregressive Integrated Moving Average (ARIMA) model 2) using that model to remove autocorrelation from the data, and 3) applying control charts to the residuals (Montgomery D.C., 2013). This type of control charts are called as special cause control (SCC) chart.

In this paper, SCC chart was applied to an autocorrelated data and comparison of the occurrences of the out of control signals appeared on both IC chart and SCC chart was made.

2. SPECIAL CAUSE CONTROL CHARTS

Autocorrelation is the linear dependence of a data set with itself. The autocorrelation function (ACF) measures how a time series is correlated with itself at different lags. The partial autocorrelation function (PACF) gives the partial correlation between values that are k intervals apart.

The traditional use of quality control charts assumes time-independence of data. In case of dependency between data, the autocorrelation structure is captured by using Autoregressive Integrated Moving Average (ARIMA) model. ARIMA models are fitted to the time series data either to better understand the data or to predict future points in the series. These models are shown as ARIMA (p,d,q) where p is the number of autoregressive terms, d is the number of times the series has to be differenced before it becomes stationary and q is the number of moving average terms. ACF and PACF are examined to identify the model parameters.

After the ARIMA model has been estimated and validated, the residuals from this model meet the assumption of independence. Therefore, the problem of the autocorrelation of the original observations is overcome and the traditional control charts can be applied to the residuals. This type of control charts are called as Special Cause Control (SCC) Charts or Forecast-Based Residual (FBR) Charts. Using SCC chart has the advantage that it can be applied to any autocorrelated data even if the data from a nonstationary data (Karaoglan and Bayhan, 2011).

3. CASE STUDY

High quality drinking water is defined as aesthetically appealing water, free of both pathogens and chemical contaminants. The primary purpose of monitoring water treatment plants is to safeguard the required water quality and to prevent related health risks. Monitoring and control are indispensable actions for ensuring th e production of high quality drinking water. It is required that the water treatment process is in statistical control and capable of meeting drinking water specifications.

Oxidability, also referred to as permanganate index, is mainly used to characterize the quality of drinking water. It is a conventional measure of contamination of water with organic and oxidable inorganic matters. Since oxidability is an important parameter to evaluate the organic pollution for water sources, it is very important to monitor the variations in this measure by using control charts and to analyze this variability on the base of specifications. As long as the control chart does not indicate the existence of an out-of-control state, the process is accepted to be operating under statistical control.

Elevli et al. (2014) draw control charts for oxidability data of 4 months between the date of August 2013 and November 2013 obtained from the monthly reports of Samsun Metropolitan Municipality General Directorate of Water and Sewage Administration. In this study, same data was used to show the effect of autocorrelation on traditional control charts in detail.

Autocorrelation plot given in Figure 1 shows the estimated autocorrelations between values of oxidability at various lags. It represents the degree of similarity between given values and a lagged version of itself. If the 5% significance limits do not contain the estimated autocorrelation at a particular lag, it is concluded that there is a significant correlation at that lag at the 95% confidence level. Figure 1 indicates a high degree of positive correlation for consecutive data points that do not die out quickly. Since the data is also non-stationary, which means observations don’t vary around a fixed mean, differencing is required.

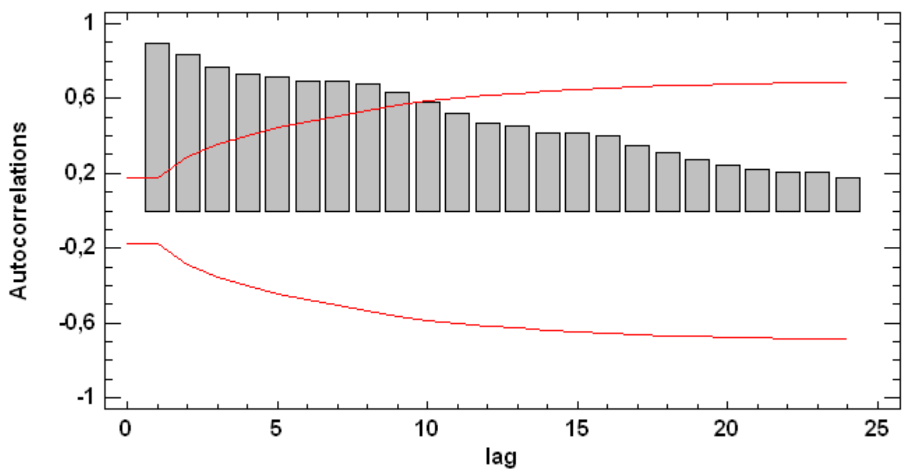

Figure 1. Estimated Autocorrelations for Oxidability Data

Figure 2 and 3 give the plots of autocorrelation and partial autocorrelation for the data taken first difference to remove nonstationary behavior. Since the ACF and PACF die out rapidly after first lag, there is no indication for the presence of non-stationarity anymore. That is, no further differencing is necessary and the number of times the series has to be differenced (d) can be taken as 1.

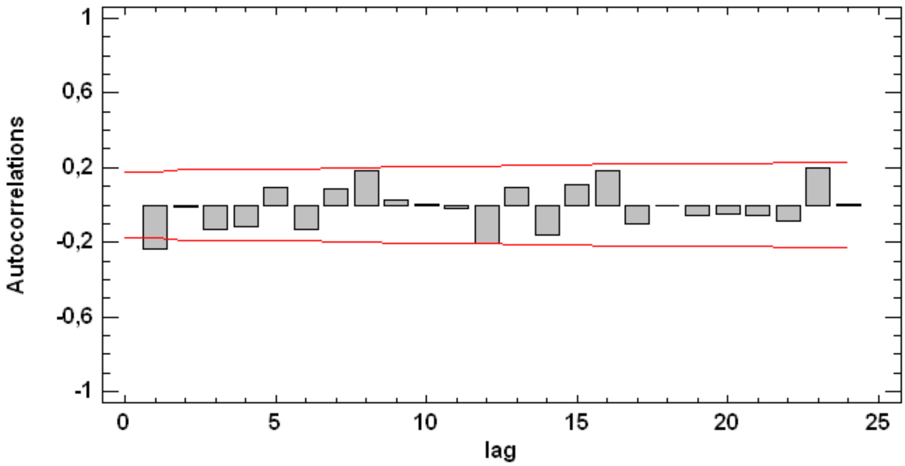

Figure 2. Estimated Autocorrelations for Oxidability_d

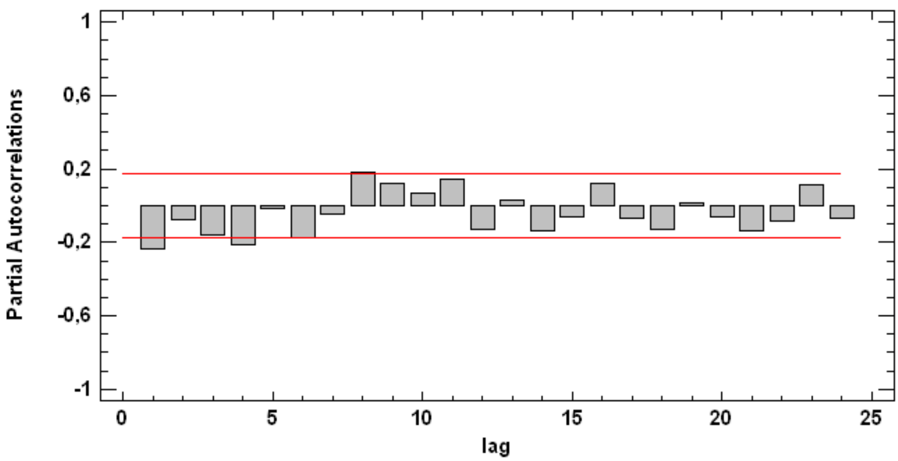

Figure 3. Estimated Partial Autocorrelations for Oxidability_d

According to Figure 2 and 3, ARIMA(1,1,1) is suitable for the oxidability data set. Statistically significant parameters of this model at 5% level are given in Table 2.

Table 2. Model Summary

Parameter	Estimate	Std. Error	t	p-value
AR(1)	0.41403	0.17114	2.41923	0.01708
MA(1)	0.72073	0.12081	5.96563	0.00000
Mean	-0.00785	0.00554	-1.41526	0.15963
Constant	-0.00460			

Figure 4 and 5 show that residuals of the model are uncorrelated and random, meaning ARIMA model is suitable for data. Therefore the residuals of ARIMA model can be used to create control charts.

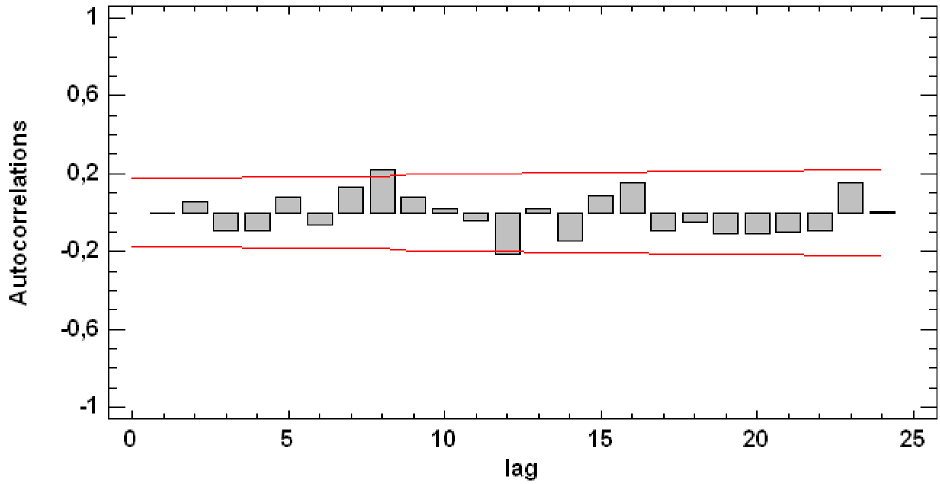

Figure 4. Residual Autocorrelations for adjusted oxidability ARIMA(1,1,1) with constant

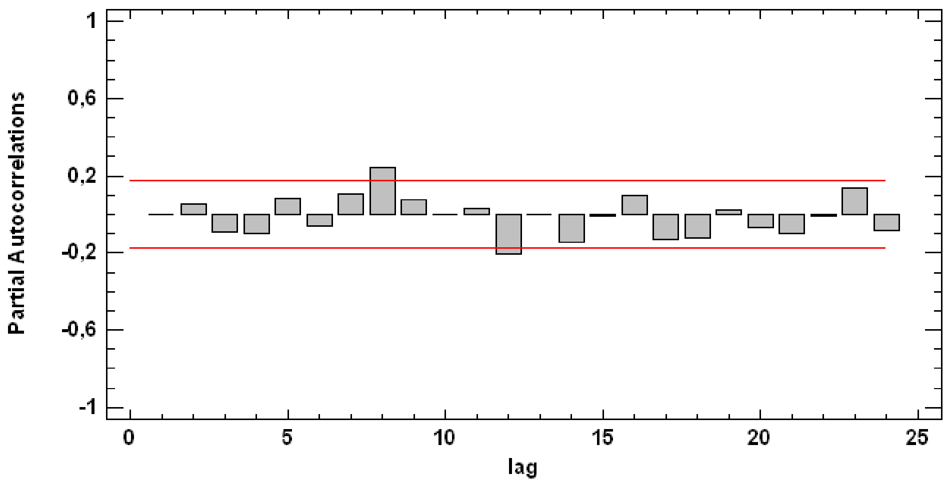

Figure 5. Residual Partial Autocorrelations for adjusted oxidability ARIMA(1,1,1) with constant

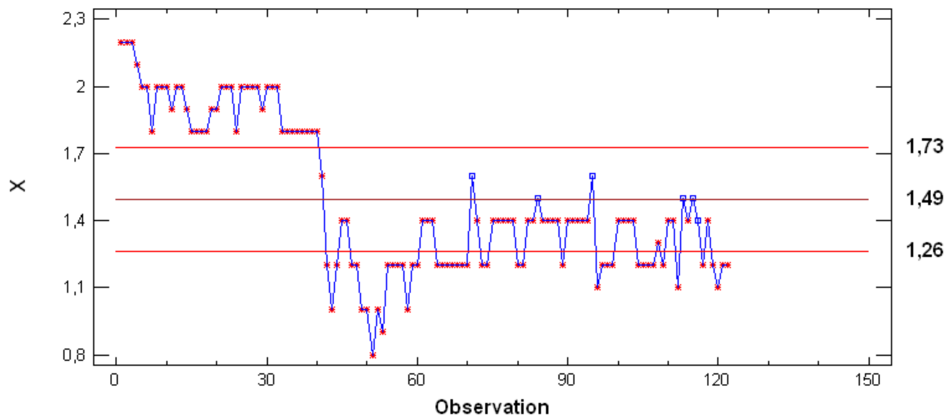

Figure 6. Individuals Control Chart for Oxidability

Control charts for the original observations and the residuals of ARIMA model are given in Figure 6 and Figure 7 respectively. According to both charts, process is not under statistical control. Of the 121 observations, 3 are beyond the control limits of SCC chart. Traditional chart gave more out-of-control signal than SCC chart because of the tighter control limits resulting from autocorrelation.

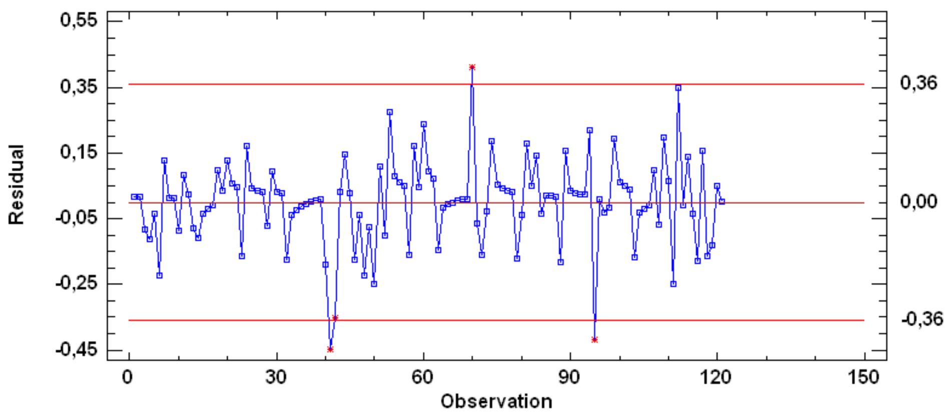

Figure 7. Special Cause Control Chart (ARIMA Residual Chart) for Oxidability

4. CONCLUSION

When independency assumption is not met, excessive number of false alarms appear in traditional control charts loosing ability to detect an assignable cause. SCC charts provide an improved method for examining process stability by enhancing the ability of practitioners to isolate and identify assignable causes of variation in case of autocorrelation existence.

According to the results, SCC chart is more appropriate for time-dependent oxidability data since it provides a higher probability of coverage than Individual Control (IC) chart. In SCC, there are three points beyond control limits indicating out of control situation. Therefore, sources of variability should be investigated and eliminated.

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