Statistical Quality Control and Improvement of Waste Water Treatment Plant

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ABSTRACT

This research studies five characteristics of water quality using techniques of Statistical Quality Control as applied to actual 2014 data collected for a water treatment plant located in United States. An overview of some of the results obtained using Minitab 17 are presented as well as conclusions and future directions of the research.

Keywords: Statistical Quality Control (SQC), Carbonaceous Biochemical Oxygen Demand (CBOD), Total Suspended Solids (TSS), Ammonia Nitrogen (NH3-N), pH

1. INTRODUCTION

This paper discusses the attributes of water quality as determined by the five following characteristics of Ammonia Nitrogen (NH3-N), pH, Total Suspended Solids (TSS) and Carbonaceous Biochemical Oxygen Demand (CBOD) or Biochemical Oxygen Demand (BOD) and Temperature as applied to 2014 actual data from a water treatment plant in the United States that asked to be not identified. A survey of the application of statistical techniques for discrete data are applied and a selection of the visualization plots generated using Minitab 17 are presented in each of the following sections for each of the 5 selected variables of water quality as indicated above.

2. BACKGROUND

Related work on the subject of this paper has appeared in book on modelling of wastewater treatment systems by Olsson & Newell (1999), multivariate statistical evaluation of spatial and seasonal variations of surface water quality by Pejman et al. (2009), and others such as Aguado & Rosen (2008), Aguado et al. (2006), Ahmad & Reynolds (1999), Al-Lahham et al. (2003), Berthoues et al. (1989), Boger (1992) for neural network applications, Charef et al. (2000), Lee et al. (2008), Reba et al. (2013), Rosen et al. (2001), Shen et al. (2009), Shrestha & Kazama (2007), Siqua et al. (2000), Yin et al. (2005), Yoo et al., (2003).

3. ANALYSIS OF WATER QUALITY VARIABLES

3.1 Carbonaceous Biochemical Oxygen Demand (CBOD)

Carbonaceous Biochemical Oxygen Demand (CBOD) is the rate at which organisms use the oxygen in water or wastewater to while stabilizing decomposable organic matter under aerobic conditions. In decomposition, organic matter services as food for the bacteria and energy results from its oxidation. Figure 1 is a Time Series plot that contains data set for the entire year of 2014 which is divided quarterly. The CBOD values are ranging between 2.0 and less than 6.0. The CBOD values are ranging between 3.0 and less than 15 which is acceptable for the CBOD effluent. This

Time series plot shows a sequence of data points from the month of January till December for 2014 year. The CBOD value should be less than 15 mg/l (ppm).

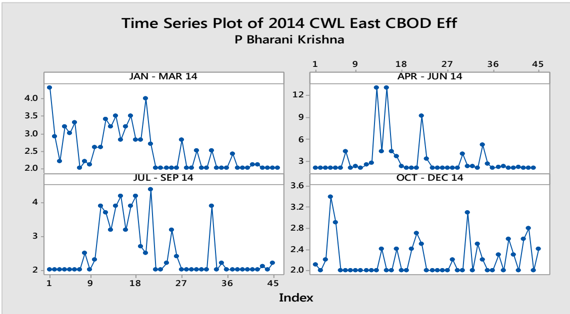

Figure 1: Quarterly Time Series of CBOD

Figure 2 is a histogram that shows most of the data points fall into the range of 2.0 to 3.0 which means basically the quality process of 2014 was operated well.

Figure 3 is probability plot for the data for months of January, April, May, July, September, October, and November that appear slightly departing from the straight line. Generally, the points on this plot form a nearly linear pattern which indicates that the normal distribution is a good model for this data set of 2014.

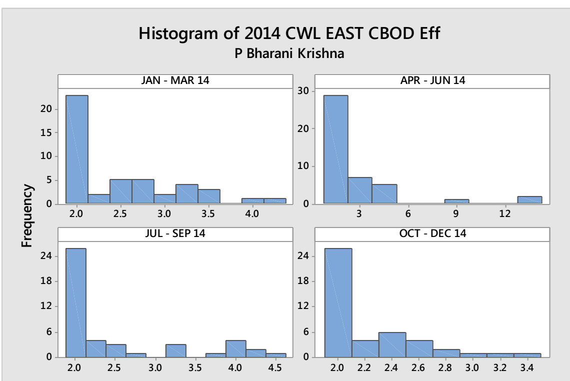

Figure 2: Quarterly Histograms of CBOD

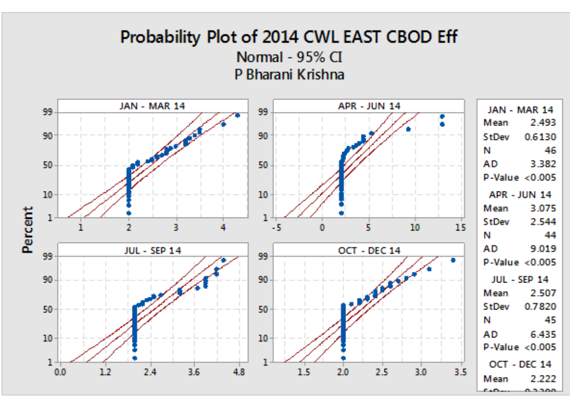

Figure 3: Quarterly Probability Plots of CBOD

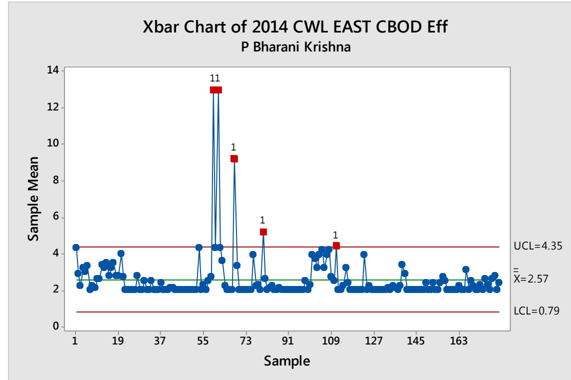

Figure 4: X-Bar Charts of CBOD

Figure 4 above is an X-Bar chart that shows that The CBOD values are ranging within the upper control limit of 4.35 and the lower control limit of 0.79.Figure 5 shows residual plots of CBOD and indicate that when temperature is between 14 and 24 and flow is below 9, the data is stable under 2.5.

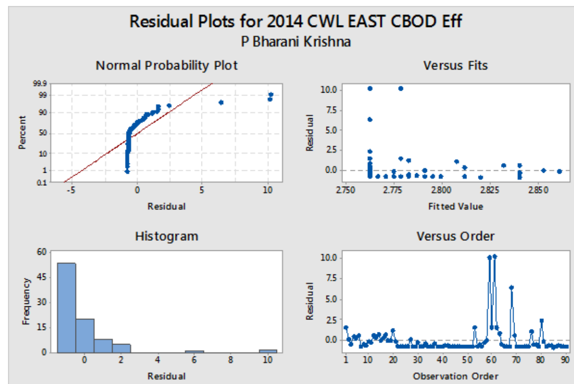

Figure 5: Residual Plots Summary of CBOD

3.2 Total Suspended Solids (TSS)

Total Suspended Solids Include a wide variety of material, such as silt, decaying plant and animal matter, and industrial wastes, can be organic or inorganic, can be dissolved and suspended, and high concentrations of suspended solids can cause many problems for stream health and aquatic life.

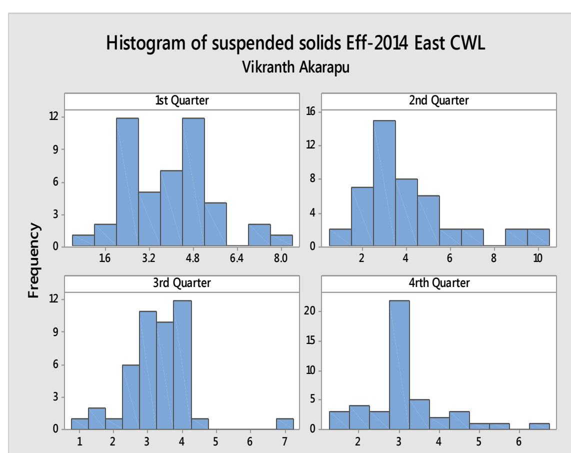

Figure 6: Quarterly Histograms of TSS

Figure 6 is a histogram and shows that the last quarter recorded the highest frequency among all the quarters which was around 20. While the third quarter showed almost zero frequency at the end of the period. The first quarter represents a bi-model and while the second and final quarters represents a single spike model. The third quarter shows us a spike with maximum frequency close to another spike. And also the TSS data is centered on a peak of 4.8 mg/l, 6mg/l, 4mg/l, and 4mg/l in the first, second, third and final quarters respectively. Which is well below the 20 mg/l monthly average TSS limit. This could indicate that TSS is not as susceptible to seasonal fluctuations.

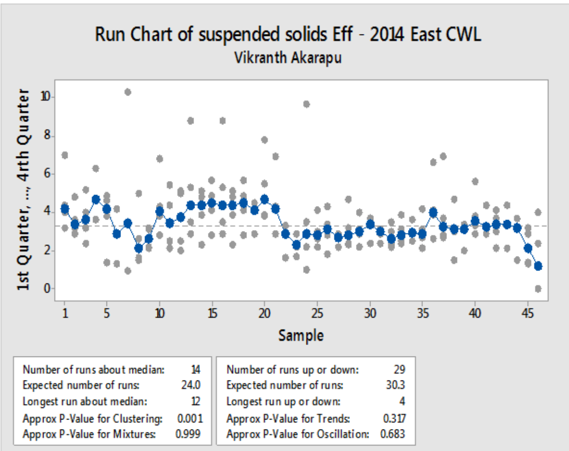

Figure 7: Run Chart of Suspended Solids (TSS)

Figure 7 is a runs chart that displays process performance of the TSS over time. Upward and downward trends, cycles, and large aberrations may be spotted and investigated. In a run chart, events, shown on the y axis, are graphed against a time period on the x axis. In the above figure, an average line (dark dotted line), representing the average of all the y values were recorded, which can easily be added to a run chart to clarify movement of the data away from the average. An average line runs parallel to the x axis. The light colored dots are all the sample values taken quarterly for the entire year. And some outliers can be easily seen in the second and final quarters.

3.3 Temperature

Figure 8 shows time series plots of the variable Temperature. This show an increase in the temperature values from the middle of the second quarter and the recordings were high. These high recordings continued for next 6months after the second quarter. It is only in the middle of last quarter that the readings started to come down. The highest reading recorded was in the third quarter which is 28, and the lowest was in the first week of first quarter which is 8.

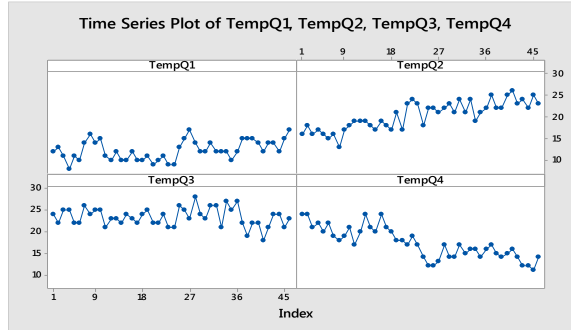

Figure 8: Time Series of Temperature Quarterly

Figure 9 shows the variable of temperature versus the variable of CBOD and attempts to determine if there is a correlation between ambient temperatures and the values of the CBOD leaving the plant. Although there were few points to look at, there does appear to be a correlation. When the temperatures are colder, the CBOD is increased. This corresponds with the high readings in the year. Likewise, when the temperatures are warmer, the CBOD levels are lower. This should indicate to personnel of water treatment plant that CBOD should be more closely monitored in winter months. They may explore taking more readings during those winter months in order to have more values to bring their monthly averages below the regulatory limit or explore solutions to taking additional measures to lower the CBOD during these months.

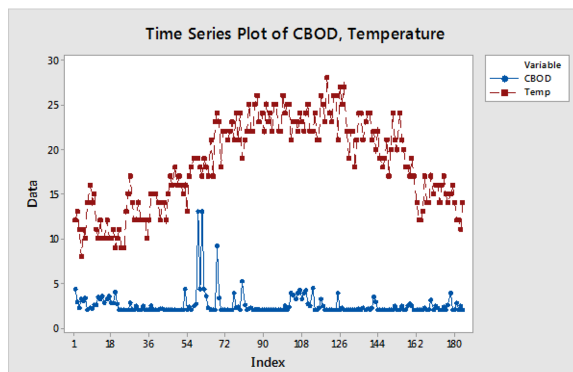

Figure 9: Times Series of CBOB & Temperature

3.4 Ammonia Nitrogen (NH3-N)

The ammonia nitrogen at east plant is analyzed three times per week and is sampled as a 6-hour composite that is flow weighted. The monthly average limit for nitrogen in water is 4mg/l(ppm). Ammonia nitrogen (N) is present in variable concentrations in many surface and ground water supplies. A product of microbiological activity, ammonia when found in natural water is regarded as indicative of sanitary pollution.

The moving average control chart for effluent ammonia (mg/l) is shown in Figure 10. This moving average analysis represents the quarterly averages for the year period. Similar to the X-bar R chart, the upper control limit generated through the moving average analysis and how this limit compares to the permitted effluent limit is of primary concern. Only two data points are above the upper control limit, however, these results are well below the permitted monthly average limit for ammonia of 4 mg/l. With these factors in mind, it cannot be said that the process is out of control based on the moving average results.

However, the moving average results do indicate an upward shift in the process that warrants further evaluation of the operational processes and plant loadings. Ammonia is rapidly oxidized by certain bacteria, in natural water systems, to nitrite and nitrate--a process that requires the presence of dissolved oxygen. Ammonia, being a source of nitrogen is also a nutrient for algae and other forms of plant life and thus contribute to overloading of natural systems and cause pollution.

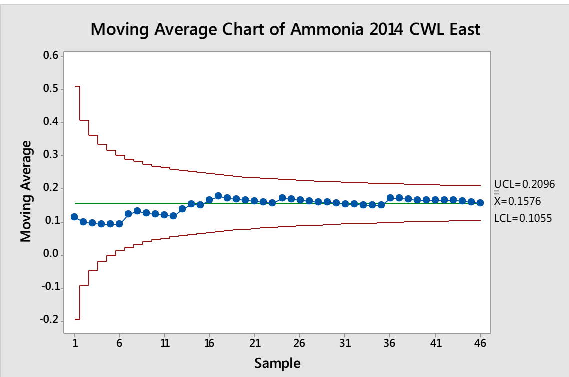

Figure 10: Moving Averages of Ammonia

Xbar-R chart as shown in Figure 11 plots the sample mean and sample range along with the control limits, if the sample mean is taken into consideration there are six points which are above the upper control limit and in sample range chart there are seven points which are above the upper control limit the process is out of control at those samples.

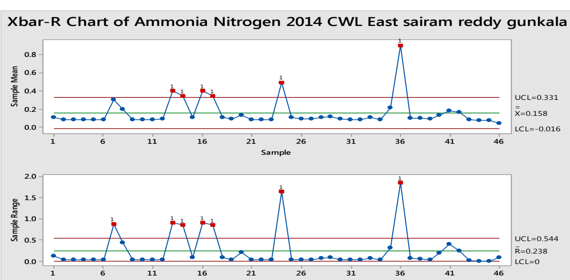

Figure 11: XBar-R Chart of Ammonia Nitrogen

3.5 pH Variable

The pH of natural waters is between 6.5 and 8.5. A measurement that is below 6 (acidic) or above 8.5 (alkaline) can disrupt aquatic life. Unlike the other variables analyzed pH has a maximum and minimum limit. A Time series plot shown in Figure 12 is a sequence of data points which is shown quarterly for 2014 year. The pH value for water (H_2O) is 7.0. If the waste water plant manages to drag the pH value of waste water somewhere close to 7.0 then they have done a good job. As this plot suggests that the pH values for the month of May, July, October and December 2014 is very close to 7.0. These values were measured at successive times spaced at uniform time intervals every Tuesday, Wednesday and Thursdays.

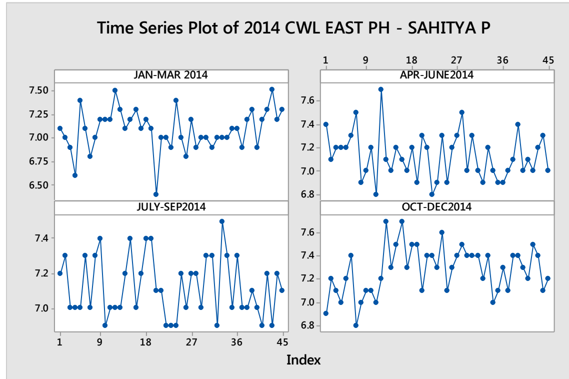

Figure 12: Time Series of pH

The plotted graph of Figure 12 shows the Time Series Plot that is depicts the data quarterly for the year 2014. In January-March and October – December, there are irregular variations on the value of pH when compared to the months of April-June and July-September.

Figure 13 shows a moving average chart for pH values that helps analysts track the pH value movements of water for the waste water treatment plant. It shows average daily settlement readings for 2014 year, and shows a few out-of-control values for samples at approximately 5, 20 and 150 to 153.

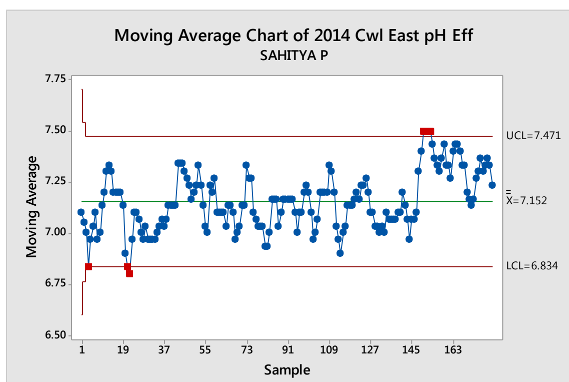

Figure 13: Moving Averages of pH

4. CONCLUSIONS

This paper has presented some applications of statistical quality control (SQC) as presented in text Montgomery (2013) to actual 2014 data as provided by a utility company that asked to remain anonymous in name to determine if in compliance to the State's Department of Environmental Quality standards. The statistical analysis using Minitab 17 provided evidence of where the discrepancies were located and problem areas that needed to be addressed for subsequent years. This research also provided insight into which SQC tools were most useful in determining the visual discrepancies using Minitab 17. The future directions of the research include the additional Minitab plots and analysis of the data such as Individual Value plots, lognormal probability plots, XBar-S charts, Pareto charts, and box plots.

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