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Evaluating environmental performance using statistical process control techniques

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Abstract

This paper builds on recent work on measuring and evaluating environmental performance of a process using statistical process control (SPC) techniques. We propose the CUSUM chart as a tool to monitor emissions data so that abnormal changes can be detected in a timely manner, and we propose using process capability indices to evaluate environmental performance in terms of the risk of non-compliance situations arising. In doing so, the paper fills an important gap in the ISO 14000 and TQEM literatures, which have focused more on environmental management systems and qualitative aspects rather than on quantitative tools. We explore how process capability indices have the potential to be useful as a risk management tool for practitioners and to help regulators execute and prioritize their enforcement efforts. Together, this should help in setting up useful guidelines for evaluating actual environmental performance against the firm's environmental objectives and targets and regulatory requirements, as well as encouraging further development and application of SPC techniques to the field of environmental quality management and data analysis.

Keywords: Environment; Quality control; Quality management; Environmental performance evaluation; SPC; CUSUM chart; Process capability indices

1. Introduction

The potential for operations research and operations management to make important contributions to environmental management practice has been increasingly recognized by academics and practitioners alike, as witnessed (among others) by recent or forthcoming special issues in journals such as *European Journal of Operational Research* (volume 102, 1997, and a focused section on reverse logistics is forthcoming), *Computers & Industrial Engineering* (Gupta and Flapper, 1999), *Journal of Electronics Manufacturing* (Gupta, 1999), and *Production and Operations Management*. Several reviews also testify to this effect; see, for instance, Bloemhof-Ruwaard et al. (1995) and ReVelle (2000) for applications of OR to environmental management, and Angell and Klassen

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(1999) for links between operations management and environment. One area in which OR has clear potential has been largely neglected, though: the application of statistical process control (SPC) tools to environmental process control and management. The potential has been noted before (for instance, in Corbett and Van Wassenhove, 1993, 1995), and Madu (1996) offers a deeper discussion of how a broad range of quality control methods, including control charts, can be applied to environmental management. The current paper builds on this by discussing environmental applications of SPC in greater detail. In particular, process capability indices are very promising and have (to our knowledge) not been discussed in this context before.

In many countries, the costs of pollution have risen dramatically during the past decades. Some major accidents such as Bhopal and the Exxon Valdez have been well publicized, with their total costs running into several billions of dollars. Small accidents, though they may only affect the local community, clearly also carry a cost to the firm, especially if they occur too frequently. And even relatively small emissions in excess of local regulations can be very costly to firms through taxes and penalties. Exceeding the amount of SO_2 or NO_x emissions permitted, or releasing higher concentrations of heavy metals into the local river, can lead to substantial fines, civil and criminal lawsuits, and even partial or full shutdown of the offending process. Striking the right balance between tight control of these processes while still maintaining efficiency is precisely the purpose of SPC.

Two key approaches to environmental improvement commonly found in the literature are environmental management systems standards such as ISO 14000 (see e.g. Marcus and Willig, 1997) or EMAS (which requires more public disclosure of environmental performance data), and the Total Quality Environmental Management (TQEM) philosophy. ISO 14000, largely analogous to the widespread ISO 9000 series of quality management systems standards, was introduced in Fall 1996, and by the year 2000 over 13,000 companies worldwide had already sought ISO 14000 certification. Early evidence suggests that there is significant overlap between ISO 9000 and ISO 14000, not just in how the standards are designed but also in drivers of diffusion (Corbett and Kirsch, 2001). Environmental Performance Evaluation is a key aspect of ISO 14000; indeed, clause 4.5.1 (Monitoring and Measurement) of ISO 14000 requires that a firm implement "documented procedures to monitor and measure on a regular basis the key characteristics of its operations and activities that have significant impacts" (Kuhre, 1998). With the increasingly widespread adoption of ISO 14000 and of environmental management systems more generally, many firms now have much more detailed data on environmental performance of their processes than ever before, but often do not know how to use such data to help control their processes.

The observation underlying "Total Quality Environmental Management" (TQEM) is that many of the concepts used in Total Quality Management (TQM) should also help manage environmental impacts, as explained in more detail in Madu (1996) and Angell and Klassen (1999). TQM can be viewed as a holistic approach to quality management, including continuous improvement, proper training and empowerment of workers, appropriate incentives, quality management systems, and extensive use of SQC techniques to support all this. TQEM carries the same philosophy into the environmental realm. However, most discussions of this analogy so far have focused on the "softer" aspects of TQM. While all these are undeniably important, the quantitative tools associated with statistical process control methods are a key ingredient of TQM, but one that has hardly been explored in the TQEM literature. A valuable exception is Madu (1996), who does explain how control charts can be used for environmental monitoring.

The current paper builds on that by showing how process capability indices can be useful for quantitatively evaluating environmental performance of a process with respect to prevailing regulation. This is an important risk management tool for practitioners, as it helps identify which processes are at risk of provoking compliance problems, but also for regulators, as it contains useful information for enforcement. It is common for customers to ask suppliers to share their SPC charts and to reduce acceptance sampling when these SPC charts show that the suppliers' processes are in control; similarly, regulators could ask for environmental SPC charts and decide on that basis which firms need more or less frequent inspections.

Especially with all the new and detailed environmental performance data now being gathered as a result of the trend towards adopting environmental management systems and ISO 14000, applying quantitative methods as SPC is becoming far easier than before. However, there are some important differences between the quality management and environmental management contexts, which have not been highlighted to date; we discuss the implications of these differences here.

In Section 2 we review some pertinent literature on environmental management and statistical process control. Section 3 discusses how to perform measurement, monitoring and evaluation of environmental performance in the context of an example based on nitrate contamination data. Section 4 explains in detail the stepwise procedure for combining quality control charts and process capability analyses respectively for evaluating the risk of a process discharge. Section 5 offers a deeper discussion of process capability analysis in the contexts of environmental risk assessment and environmental regulation and enforcement Throughout, but especially in Section 6, we discuss how the environmental context differs from a standard application to quality control and how existing SPC techniques need to be modified accordingly. In Section 7 we discuss our findings and offer suggestions for future work.

2. Review of pertinent literature and theory

The pertinent literature for our purposes can be grouped into two categories: monitoring environmental performance, and quality control charts and related methods.

2.1. Monitoring environmental performance

Many initiatives exist worldwide to monitor air and water quality of entire regions; we only review a small representative sample here. The WHO (World Health Organization) air quality monitoring project began operation in 1973 and is part of the Global Environmental Monitoring System. Sulfur dioxide (SO_2) and suspended particle matter (SPM) data were selected for inclusion in the project as indicators of industrial pollution (Koning et al., 1982). Information on these pollutants was routinely collected from industrial, commercial and residential stations from one urban area in each of the 14 participating countries. From 1976 to 1982, the network has been extended into developing countries, to a total of 65 cities in over 40 countries. Degraeve and Koopman (1998) apply mathematical programming to determine a mix of policy measures to help achieve air quality standards in the European Union.

Others have looked at environmental monitoring at a local rather than regional level. Crockett (1997) reports on water and wastewater quality monitoring at McMurdo research station in Antarctica. Results of the effluent monitoring efforts show that concentrations of metals, particularly copper, are considerably higher than before. At the individual facility level, Friend (1998) suggests a set of metrics that may impact both profitability and environmental quality, capture and quantify eco-efficiency costs and benefits, and help managers understand and focus on tangible, yet difficult-to-quantify benefits such as innovation, etc. In order to do this, he developed eco-efficiency metrics for cost structure and input measures including the consumption of energy, water, materials and labor; the output measures include solid waste, air emissions, effluents, packaging and throughput, etc. Miakisz and Miedema (1998) report that 33 electric utility companies in the US and Canada participated in a unique environmental benchmarking program (EBP). The EBP provides each participant with ideas on how to improve its performance measures in eight different categories, such as heat rates, combustion turbines, energy savings, air emissions, and other residuals.

Pollution prevention technologies have generally been advocated as holding potential to move manufacturing operations toward sustainable development and improved environmental performance (Lewis, 1988). For various reasons, firms in Europe have historically been more proactive in pollution prevention than firms in the US who tend to rely more on end-of-pipe measures (Graedel and Allenby, 1995, p. 80). However, the Pollution Prevention Act passed in the US in 1990 explicitly states that "source reduction is more desirable than waste management and pollution, yet opportunities for source reduction are often not realized" (Freeman, 1995, pp. 28–29). Measures of performance have grown more varied over the past two decades, as different stakeholders seek to assess a broad range of environmental impacts. Since 1987, all US manufacturing plants are now required by the Environmental Protection Agency to publicly report all toxic pollutants released, in the so-called Toxic Releases Inventory. Carrera and Iannuzzi (1998) pointed out that many companies do not track or measure environmental costs and therefore do not know their true environmental costs. Applying SQC methods as advocated here can help firms measure and interpret their environmental impacts and associated costs much more meaningfully.

2.2. Quality control and environmental management

The term "Total Quality Environmental Management" (TQEM) has come into vogue in recent years, as witnessed by the large number of articles on the subject and even journals bearing that name (*Total Quality Environmental Management* and *Environmental Quality Management*). The underlying philosophy of TQEM is that the principles of TQM apply to environmental improvement too (Angell and Klassen, 1999). Though the potential of applying quality control tools to environmental management has been pointed out before (Corbett and Van Wassenhove, 1993, 1995; Madu, 1996), the current paper goes beyond those works by highlighting the potential of process capability indices as a tool for environmental performance evaluation, and by offering a more detailed discussion of the differences between the quality control and environmental management contexts and the consequences for carrying SPC tools developed for the former arena over into the latter arena. The extensive review by Angell and Klassen (1999) supports our belief that these questions have not yet been explored.

ReVelle (2000) states that operational research has been usefully applied to a wide variety of environmental problem areas including water resource management, water quality management, solid waste operation and design, cost allocation for environmental facilities, and air quality management. Despite almost four decades of such activity, challenging operational problems remain in all of these areas. A similar argument can be made about the application of modern statistical process control charts and related methods to the field of environmental quality management since these techniques still remain unfamiliar to most environmental personnel. Although control charts have gained considerable acceptance for some types of quality checks familiar to environmental chemists (Juran and Gryna, 1993), they are less frequently applied in environmental monitoring. One reason for this lack of use is that most references emphasize control charts for mean and range ($\overline{X}$ and R charts) which are not usually applicable since environmental samples are not commonly run in replicate.

Woodall and Montgomery (1999) provide an overview of current research on control charting methods for process monitoring and improvement. They offer a historical perspective along with ideas for future research. Woodall (1997) presents a comprehensive bibliography on control charting methods using attribute data, for example, p, np, c and u charts, which might be applicable for monitoring qualitative environmental indicators. Performance of control charts is commonly evaluated based on their average run length (ARL), the average number of samples required to detect an out-of-control point. Exponentially weighted moving average (EWMA) control charts are developed for monitoring the rate of occurrences of rare events based on the interval times of these events. Gan (1998) provides a simple procedure for determining the parameters of a one-sided or two-sided EWMA chart. Cumulative sum (CUSUM) charts, first proposed by Page (1954) and studied since by many authors, have proven to be very effective in detecting small process shifts. Both Gan (1998) and Pan and Lin (1999) found the CUSUM chart to be optimal for detecting shifts in the process mean, while the EWMA chart is found to be slightly less sensitive due to subjective selection of the smoothing constants.

Each control chart method has its advantages and disadvantages. Some authors (Montgomery, 1980, 1996; Woodall and Montgomery, 1999) use economic criteria to determine optimal chart parameters. Montgomery (1980) presents a comprehensive review and survey on these economic decision models. Ho and Case (1994) also provide a brief literature review on economic design of control charts. These economic control charts have not yet been widely applied in practice, primarily due to the difficulty of arriving at reliable estimates for the cost parameters involved. However, in the case of emissions monitoring, the cost of an out-of-compliance situation is often defined precisely by the prevailing legislation, in the form of penalties and taxes for excess emissions. Further exploration of economic control charts for environmental process control is a promising area for future research; for the moment, we start with exploring how to modify conventional control charts and process capability analyses for environmental purposes.

3. Measurement, monitoring and evaluation of environmental performance

Here, we first outline the general problem of environmental process control and evaluation. We start with some issues related to measurement, then monitoring using modified control charts, and performance evaluation using process capability indices.

3.1. Measurement

Accurate measurement is naturally a prerequisite for meaningful process control, and measurement of environmental performance indicators is even more challenging than it is for traditional quality control purposes. Contamination is a common source of error in all types of environmental measurements. Most approaches present numerous opportunities for sample contamination from a variety of sources (Lewis, 1988). This section addresses the problem of assessing and controlling sample contamination. A similar approach may also be applied to other types of environmental problem, such as air and water quality monitoring, as long as the key quality characteristics and their specification limits are clearly defined. Lewis (1988) indicates that equipment and apparatus, sampling in the field, sample containers, ambient, glassware, and reagents, etc., are common sources of contamination. The most commonly used analytical tools for assessing and controlling sample contamination are blanks. According to Lewis (1988), there are three types of laboratory blanks: system, solvent and reagent blanks for assessing and controlling many types of laboratory contamination. There are also three types of field blanks: matched-matrix, sampling media, and equipment blanks, which are used to provide information about contaminants that may be introduced during the sample collection, storage, and transport. Regardless of the types of blank used for the application, one should minimize the potential risk for inadvertently introducing contamination during the preparation of the blank or at any other point where the actual samples are not exposed to a similar opportunity for contamination. When properly used, blanks are very effective tools for assessing and controlling sample contamination and in adjusting measurement results to compensate for the effect of contamination (Lewis, 1988). Whether blank data are used primarily for ongoing process control or for retrospective assessment, Shewhart charts (mean and range or mean and standard deviation, i.e. $\overline{X}$–R or $\overline{X}$–S) and other types of control charts provide the most effective tools for monitoring and interpreting the blank results.

3.2. Monitoring

Process control using control charts typically involves two phases (Gan, 1998; Montgomery, 1996). A process being "in control" implies that the process is stable and the probability distribution does not vary significantly over time. A control chart would be a test of the hypothesis that the probability distribution of observation x is stationary, i.e. the mean of the distribution is constant. In general, the population mean will be unknown. The first period of the data analysis, also called the base period, is used for estimating the population mean as well as for establishing the tentative or trial upper control limit (UCL) and lower control limit (LCL). Any out-of-control points for which assignable causes can be found should be removed or eliminated before the trial control limits are calculated. Depending on how, when and where the measurements are taken, one may need to look beyond the boundaries of the process itself for assignable causes, further than one would normally do in the context of quality control.

These estimated values are used for the subsequent period, known as the monitoring period. The estimated population mean obtained during the base period continues to be used during this period. Any rejection of the hypothesis that the process mean remains unchanged would be called "process out of control" or "lack of control", indicating that the process is unstable. Shewhart control charts are based on the Central Limit Theorem, which means the sampling distribution will follow the normal distribution, regardless of the shape of the underlying population distribution when sample size n is sufficiently large. If the population distribution is symmetric, then even with $n = 4$ or 5, the sampling distribution tends to approach the normal distribution. However, as most environmental data, such as blanks for contamination, are not commonly run in replicate, the Shewhart control charts for means and ranges are not usually applicable. In this case, a special type of control chart for individual measurements based on moving ranges of observations (the so-called IX–MR chart; Wadsworth et al., 1986, p. 192), is used for monitoring the blank results. The moving range of a series of observations x_i $(i = 1, \ldots, n)$ is commonly defined as $\mathrm{MR}_i = |x_i - x_{i-1}|$ for $i = 2, \ldots, n$. Since the Central Limit Theorem cannot be applied to the distribution of individual measurements, a Lack of Fit test must be conducted on the blank measurements before setting up the control limits. Once normality of the measurements has been confirmed, the trial control limits for the individual values are commonly established as follows (Wadsworth et al., 1986, p. 192):

$$\mathrm{UCL} = \hat{\mu} + 3\hat{\sigma} = \hat{\mu} + E_2\overline{\mathrm{MR}} = \hat{\mu} + 2.66\overline{\mathrm{MR}},$$
$$\mathrm{LCL} = \hat{\mu} - 3\hat{\sigma} = \hat{\mu} - E_2\overline{\mathrm{MR}} = \hat{\mu} - 2.66\overline{\mathrm{MR}},$$

where $\hat{\mu}$ represents the process mean, E_2 is a constant which depends on the number of observations used for the moving ranges (and $E_2 = 2.66$ when consecutive pairs of observations are used), and $\overline{\mathrm{MR}} = \sum_{i=2}^{n} \mathrm{MR}_i/(n-1)$ represents the average of the moving ranges.

3.3. Evaluation

If the blank measurements are within the UCL and LCL and only a random pattern of variation occurs, then this process is said to be in statistical control or stable. As long as the blank results are in control, then process performance can be predicted by process capability analysis. Process capability analysis compares the inherent variability of the process with the specification limits, in our case emission limits, so that the environmental performance potential can be detected under normal, in-control conditions. The process capability index, defined as $Cp = (\mathrm{USL} - \mathrm{LSL})/(6\hat{\sigma})$, where $\hat{\sigma}$ is the estimated standard deviation of the process under statistical control, is the specification range divided by the process spread. It measures potential capability, assuming that the process average is equal to the midpoint of the specification range and that the process is in control (Juran and Gryna, 1993). Using $6\hat{\sigma}$ as the denominator is equivalent to defining the Cp index to be equal to 1 whenever the specification limits are three process standard deviations away from the mean. This has been found to be a useful benchmark for quality applications; for environmental control purposes, it is unknown whether a different range than $6\hat{\sigma}$ might be more appropriate. More experience is needed with different processes and regulatory environments in order to determine suitable benchmarks for the environmental case.

In environmental contexts, however, one normally only faces an upper specification limit (USL); there is of course no lower specification limit for minimum emission levels. In such a case, the Cp index is given by $Cp = (\mathrm{USL} - \hat{\mu})/(3\hat{\sigma})$. The Cpk index, on the other hand, reflects the current process mean's proximity to the USL or LSL. Cpk is estimated by

$$Cpk = \min\{(\mathrm{USL} - \hat{\mu})/(3\hat{\sigma}), (\mathrm{LSL} - \hat{\mu})/(3\hat{\sigma})\}$$

(Juran and Gryna, 1993). When no Lower Specification Limit exists, $Cpk = (\mathrm{USL} - \hat{\mu})/(3\hat{\sigma}) = Cp$. Montgomery (1996) shows several values of the Cp indices, along with the associated values of process fallout, expressed in non-conforming parts per million (ppm). These potential process defectives or fallouts were calculated based on a normal distribution of the key quality characteristics. For example, $Cp = 1.0$ indicates there will be 1350 ppm for USL only and 2700 ppm for a two-sided specification; $Cp = 0.5$ indicates 66,807 ppm and $Cp = 1.3$ indicates 48 ppm for one-sided specifications, etc. The potential risk of process contamination can thereby be determined.

The Shewhart and IX–MR charts are most effective for detecting contamination when measurement variability is small relative to the level of contamination to be detected. However, many measurements may be required to be able to detect small sustained shifts in the process mean. CUSUM charts are better tools for detecting small shifts of the process mean compared to the other candidates, such as EWMA charts (Gan, 1998; Pan and Lin, 1999). The traditional CUSUM chart directly incorporates all the information in the sequence of sample values by plotting the cumulative sums of the deviations of the sample values from a target value (Hansen and Ghare, 1987; Montgomery, 1996). To better understand the basic principles of CUSUM charts, let x_j denote the measurement of the jth sample blank and let μ be the target for the process mean. The CUSUM chart is then formed by plotting the cumulative sum up to and including the ith sample, i.e. plotting the quantity $S_i = \sum_{j=1}^{i} (\bar{x}_j - \mu)$ against the sample blank number i. Normally, one uses a V block or mask to detect process shifts. If the process mean shifts upward or downward, out-of-control points will lie outside the upper or lower arm of the mask. In the following example, we demonstrate the use of CUSUM charts for process monitoring and apply process capability concepts for assessing the potential risk of contamination.

4. An application of environmental control charts

In this section, we describe a step-by-step procedure for applying environmental control charts and performing process capability analysis; we illustrate the procedure using nitrate concentration data from Lewis (1988).

4.1. Step 1. Identify the key process indicators and metrics

Clearly, identifying which process indicators need to be monitored is a critical first step. Several criteria play a role in identifying these key process indicators:

- *Regulation*: any emissions that are subject to regulatory limits should be constantly monitored and controlled, to minimize the number of non-compliances and hence penalties or other negative consequences.
- *Risk*: any process variables that are indicators of potential accidents should also be selected, as part of an effective risk management program.
- *Public awareness*: some types of emissions are not subject to regulatory limits as such, or the level of emissions at the facility in question may be well within the limits specified, but if emissions are tracked and publicly reported, firms may wish to monitor and control them anyway. For instance, the Toxic Releases Inventory (TRI) data on emissions of all facilities above a certain size, collected by the EPA in the US, are now available on the Internet through the Environmental Defense Fund's website at www.scorecard.org.

Practitioners who have gone through the process of implementing an environmental management system, especially along the lines of ISO 14001, often find that this step, known as "identification of aspects and impacts", is the most challenging. For many firms, especially less-heavily regulated firms, it is the first time they attempt to systematically identify all areas in which they have significant environmental impact, and to measure that. Such impact assessments are often somewhat subjective in nature; the SPC-based approach we advocate here allows a far more quantitative and precise measurement.

4.2. Step 2. Collect the data using an appropriate data sheet

After selecting the key process indicators to be monitored and controlled, the nitrate concentration level in our example, we usually need 20 samples to develop the trial limits (see for instance Wadsworth et al., 1986, p. 191). The data, from Lewis (1988), are shown in Table 1. The first 20 nitrate concentration blank results correspond to phase I (the base period); blank results 21–60 represent the subsequent blank measurements for phase II (the monitoring period).

4.3. Step 3. Examine the distribution of the historical data and perform an appropriate transformation, then plot the data onto an IX–MR chart or other suitable charts

Since the original 20 historical data are significantly skewed, the raw data were transformed by taking the natural logarithm of each value. After this transformation, the data show significant improvement in the normality test. The Kolmogorov–Smirnov test statistic for normality with Lilliefors significance level is 0.13, less than the critical value of 0.294 (for $n = 20$ at 5% significance level). In other words, we cannot reject the hypothesis of normally distributed disturbances, but given that the sample size is only 20, we cannot confidently accept the normality hypothesis either. The Shapiro–Wilks statistic is 0.902 with corresponding p-value of 0.0466, suggesting that we marginally reject the hypothesis of normality at a 5% significance level but would accept it at any higher level. Fig. 1 shows the IX–MR charts for the transformed nitrate concentration data. If the logarithm, inverse and square root transformations (the most common ones) fail, we might consider using the Johnson transformation (Pan and Lin, 1999; Polansky et al., 1999) to transform non-normal data to normal data.

4.4. Step 4. Establish the trial control limits for the IX–MR charts by eliminating the out-of-control points

To develop trial limits for future monitoring, we must eliminate the out-of-control points whenever there exist special causes of variation (assignable causes) for these points, as they cannot be considered normal conditions for the process. We first eliminate the outliers for the MR chart and check the stability of the chart, then remove the outliers for the IX chart and check for the stability too. As one can see from both IX and MR charts shown in Fig. 1, observation 11 is an outlier as it lies above the tentative UCL. Fig. 2 shows that, after removing the outlier, the IX–MR charts passed the stability test for both the mean and variability. Therefore, the trial control limits for the IX–MR charts can be

Table 1
Nitrate blank measurements data from Lewis (1988)

Phase I	0.033	0.049	0.002	0.002	0.008	0.002	0.014	0.016	0.009	0.009
	1.631	0.063	0.042	0.022	0.093	0.022	0.002	0.002	0.031	0.004
Phase II	0.006	0.028	0.021	0.020	0.031	0.002	0.002	0.026	0.040	0.726
	0.081	0.089	0.128	0.053	0.019	0.353	0.353	0.389	0.066	0.731
	0.283	0.277	0.213	0.452	0.288	0.051	0.056	0.253	0.054	0.097
	0.672	0.221	0.206	0.293	0.128	0.431	0.180	0.108	0.052	0.216

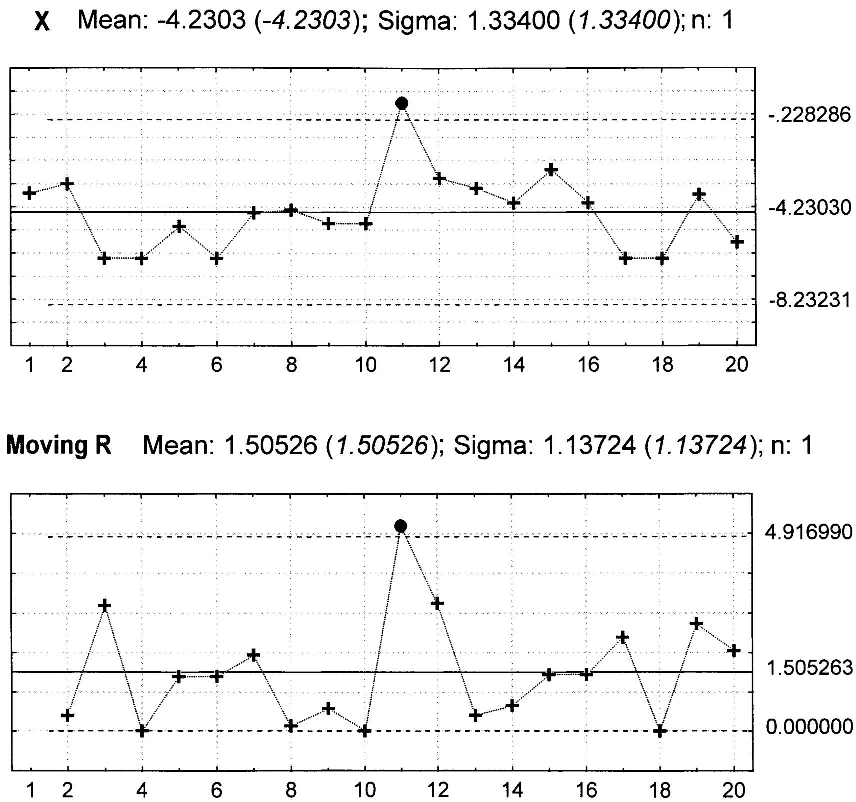


Fig. 1. IX–MR charts for nitrate blank measurements (phase I).
Note: The top chart contains the IX chart, the lower chart contains the MR chart for the nitrate concentration data (after logarithmic transformation) during the trial period (phase I). The dotted lines indicate the tentative LCL and UCL.

determined. The normality tests also improve after eliminating the outlier.

4.5. Step 5. Perform the initial process capability analysis for phase I (the base period) to justify the baseline for assessing the environmental risk

Fig. 2 shows that the nitrate blank process is in statistical control, so a process capability analysis can be performed to determine the *Cp* and *Cpk* indices. In the nitrate concentration example, only an USL is given, with USL = 1%. Note that the USL for the transformed data is USL = ln(1) = 0%. The top chart in Fig. 3 shows that the transformed nitrate concentration data follow a normal distribution and that $Cp = Cpk = 1.141$, which means the process fallout is approximately 320 ppm. Since $Cp = Cpk > 1$, we may conclude that the initial process capability with respect to contamination risk is quite low. The probability of rejection (i.e. a nitrate concentration that is not in compliance with the USL) is 0.032%.

4.6. Step 6. Use the CUSUM chart for detecting small sustained shifts of the process mean if necessary

The top chart in Fig. 4 shows the IX chart for phase II (the monitoring period). Note that the trial limits are based on Step 4 (Section 4.4). The lower chart in Fig. 4 indicates that the CUSUM chart can be applied for early detection of process changes. The V block shows that the process mean

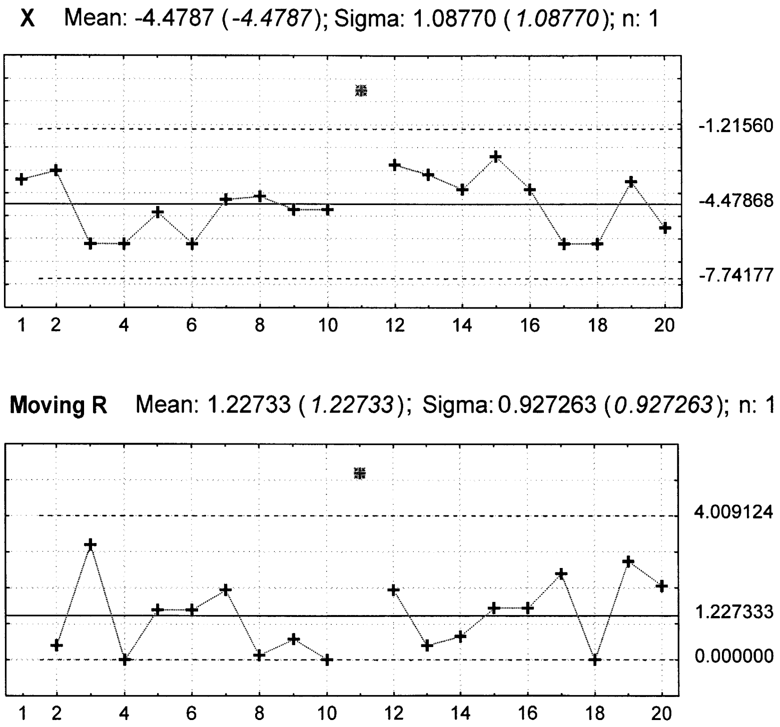


Fig. 2. Setting up trial control limits after removing out-of-control points.
Note: The top chart contains the IX chart, the lower chart contains the MR chart for the nitrate concentration data (after logarithmic transformation) during the test period (phase I). The dotted lines indicate the LCL and UCL.

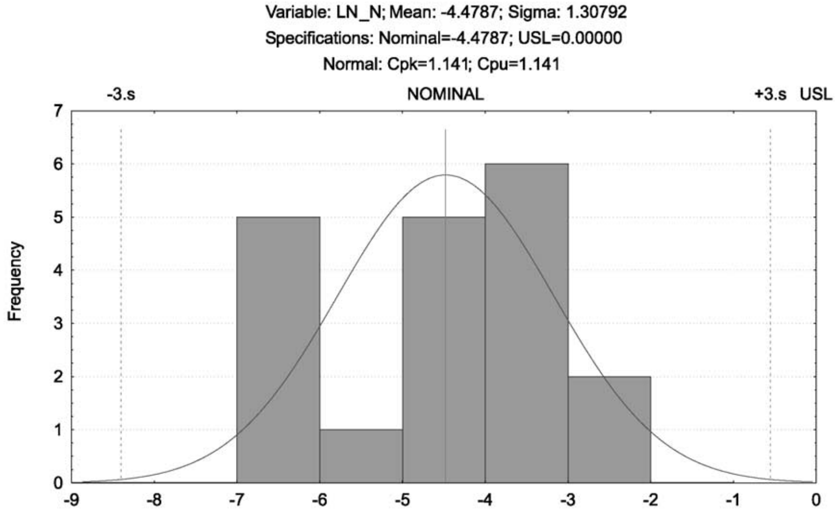
shifts downward and we can detect such a trend at point 5. Compare this to the top chart in Fig. 4, where the IX–MR chart detected the change at point 11. This illustration is consistent with the earlier observation that CUSUM charts are more effective in detecting changes in process mean than traditional IX–MR charts (Pan and Lin, 1999). In reality, this will lead the decision maker to proactively respond to the out-of-control situation and correct the problems in a timely manner.

4.7. Step 7. Continue to monitor environmental data using the trial limits and take corrective measures for out-of-control situations

Analysis of out-of-control situations needs to be addressed in order to improve the stability and capability of the process. Periodic review of the specifications in relation to the process capability should be conducted on a regular basis. The lower chart in Fig. 3 shows that the process capability has deteriorated during the monitoring period to $Cp = Cpk = 0.822 < 1$, which indicates the potential risk for unacceptable nitrate contamination levels has increased from approximately 320 ppm to approximately 8000 ppm. The probability of rejection is 0.8%, which means the environmental risk is much higher than it was during the initial baseline period. Corrective measures need to be taken to prevent future non-compliances.

5. Evaluating environmental performance using process capability indices

The procedure proposed in the previous section uses cumulative sums of observations to allow operators to detect process shifts earlier than they might be able to with a traditional IX–MR chart. In addition, the information used to construct the



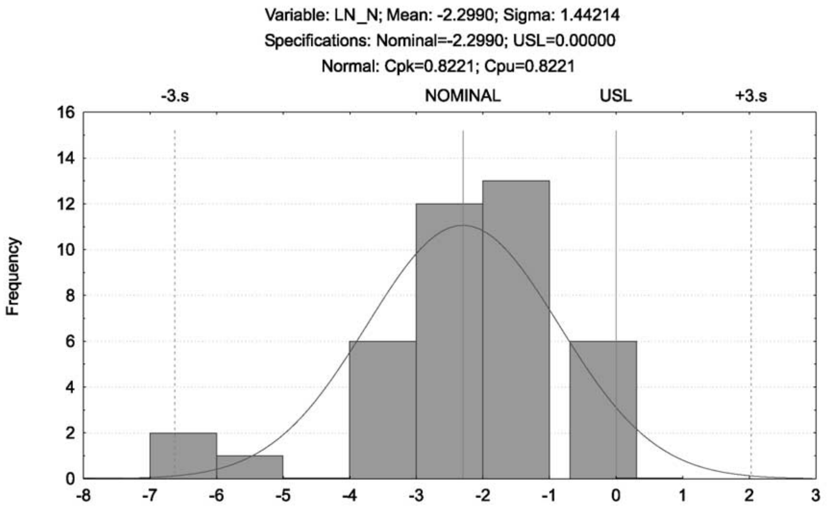


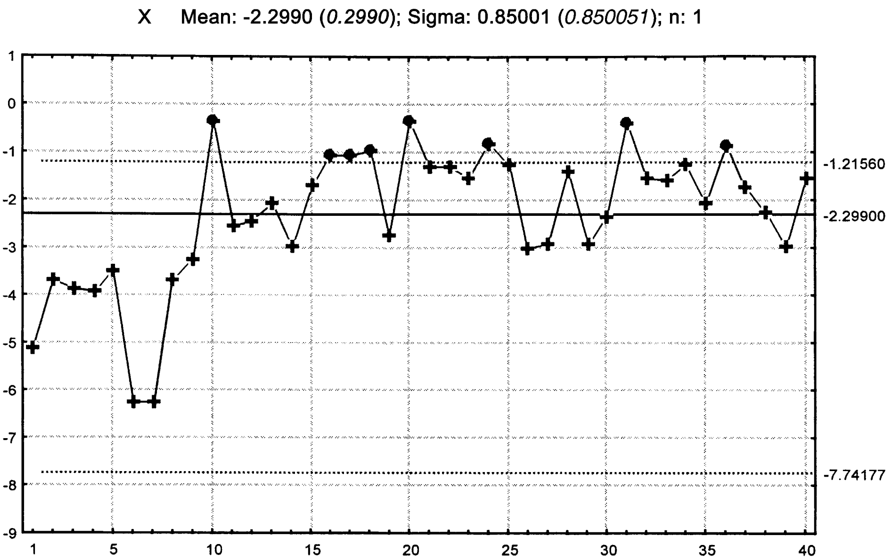
Fig. 3. Process capability analyses for nitrate concentration data.
Note: The top figure corresponds to phase 1, the trial period; the bottom figure corresponds to phase II, the monitoring period.

CUSUM chart is used to perform process capability analyses, to determine the likelihood of the process entering an out-of-control state, or, in this case, an unacceptable emissions level.

5.1. Environmental risk assessment using process capability indices

It is particularly the process capability analysis that can help decision-makers assess whether the process is capable of complying with existing environmental legislation for a sufficiently large proportion of time. We will illustrate how the process capability analysis can be used in conjunction with risk assessment tools used in a quality control context.

A well-known tool for risk assessment is failure mode and effect analysis (FMEA), as described in for instance Kolarik (1995). Sometimes a criticality analysis component is added to this, as for instance in the D1-9000 standards at Boeing. This involves



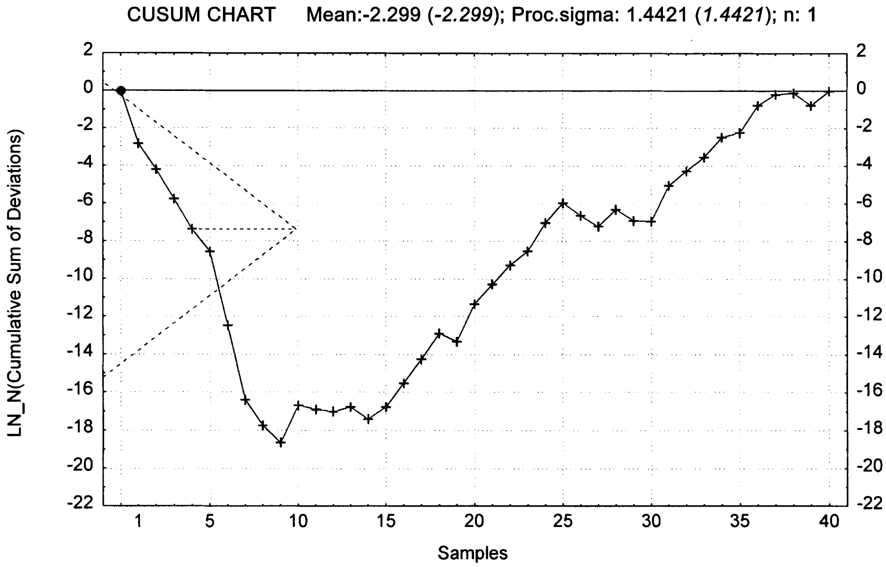


Fig. 4. Control charts for the nitrate blank measurements (phase II).
Note: The top figure shows the IX chart, the lower figure shows the CUSUM chart for the nitrate concentration data (after logarithmic transformation), for the monitoring period (phase II).

identifying each process step that may fail, then assigning rankings for occurrence probability, severity, and detectability. The "occurrence ranking" indicates how likely a failure is considered to be (where higher scores correspond to higher probabilities), and is related to the process capability indices. The "severity ranking" indicates the potential impact of a failure (with higher scores corresponding to more serious impact). The "detectability ranking" indicates how likely it is that a failure can go undetected until its full impact materializes; in the traditional quality control setting, this is the probability of shipping products containing an undetected defect. Higher scores again correspond to higher probability of defects going undetected. The three rankings are then multiplied, and higher total scores indicate higher risk.

As noted above, with a one-sided specification limit, a $Cp = Cpk = 0.5$ would indicate 66,807 ppm; $Cp = Cpk = 1.0$ indicates 1350 ppm; and $Cp = Cpk = 1.3$ indicates 48 ppm. During the failure mode and effect analysis for $Cpk = 0.5$, the occurrence ranking suggests a very high probability of occurrence. From the viewpoint of the person evaluating the process, a non-compliance is almost certain to occur; the highest-ranking score is usually assigned in such a case. However, for $Cpk = 1.3$, the probability of occurrence is remote; the lowest ranking score is usually assigned in this case. Other risk assessment tools, such as severity and detectability ranking, can also be applied to an environmental FMEA.

Though clearly the latter case corresponds to a process that is far more tightly controlled, the analysis does not tell us which capability level is required for any specific instance. Whether a $Cp = Cpk = 1.3$ is sufficient (as in many manufacturing industries) or a $Cp = Cpk = 1.67$ is needed (common in the electronics industry) depends, as always, on the cost of Type I and Type II errors. Given that the processes for which the approach proposed in this paper is most applicable will often be relatively heavy continuous and semi-continuous industrial processes, the cost of stopping the process for a false alarm might be very substantial. The cost of exceeding the emissions limits can also vary widely, depending on the type of emission, the exact legislation and measurement methods, and other factors. We are currently investigating economic design of CUSUM charts to incorporate these factors, and are also engaged in applying these links between risk assessment and process capability analysis in a chemical plant.

5.2. *Process capability indices and environmental regulation*

Another audience that could benefit from process capability analysis is formed by the regulatory community. Just as customers often inspect their suppliers' quality by requiring them to submit their control charts and other SPC analyses, regulators could assess a firm's degree of compliance by evaluating its process capability analysis. The regulator could use this in several ways. First, the process capability analysis indicates how many non-compliance situations one would expect over a given period of time; the regulator can then compare that to the number of non-compliances actually found, whether during its own monitoring efforts or audits, during third-party audits, or through the firm's self-reported environmental performance. Second, the process capability analysis can help a regulator decide where to allocate scarce monitoring and audit resources. Almost no environmental regulatory agency in the world has sufficient resources to ensure permanent compliance of all facilities under their oversight, and prioritizing their monitoring and enforcement efforts is a major challenge. A firm that can demonstrate a high process capability level would require far less frequent audits than a firm with a low capability level. Third, process capability analyses are easier to compare across firms than many other metrics are, such as number of non-compliances, total emissions, etc. This means that regulators can use process capability analyses to benchmark environmental performance of comparable firms, and can better assess when firms' complaints about (proposed) regulations being too strict are justified or exaggerated. Each of these potential uses of process capability analyses naturally also applies to third-party auditors, such as ISO 14001 auditors.

6. Differences between quality control and environmental management

We should emphasize that, although applying SPC tools to environmental monitoring has substantial potential, whether for air, water or other emissions, it is by no means a direct and standard application. There are some important differences between the quality control setting and the environmental monitoring case that apply equally to the air and water emissions cases.

First, in a majority of quality control situations, the specification limits are bilateral, i.e. deviations from the mean in either direction are undesirable. This is true whether the process involved is a packaging filling line, a machining operation, or one of many other possibilities. For environmental control, however, specification limits are always unilateral: emissions may not exceed a certain limit, but there is (clearly) no lower limit. This problem certainly has been studied in the SPC literature (see for instance Ghosh et al., 1997 or Pan and Wu, 1996), but nowhere near as extensively as the bilateral case.

Second, in traditional quality settings, the specification limits generally apply per unit, where the units are the same as the measurement units used in monitoring. On a machining operation, the aim is to avoid a single widget from falling outside the specification limits. In the environmental case, however, the specification limits depend on the prevailing legislation, and will often concern cumulative or average emissions over longer periods, whether hourly, daily, or monthly. In that case, one could be monitoring the process using daily emissions data, with no specification limits on daily emissions themselves, but only an upper limit on total monthly emissions. This complicates the design of the control chart and, to our knowledge, such a situation has not yet been studied in the SPC literature.

Third, most traditional SPC settings assume that the underlying stochastic process is univariate and stationary, producing uncorrelated observations. Data used in environmental monitoring, though, are more likely to be multivariate and/or correlated, as several types of emission are regulated and these are more heavily influenced by other common ambient factors: for instance, SO_2 and NO_x emissions are driven in part by the product mix being produced during that period, leading to significant correlation over time in emissions data and across emission types. Some recent developments in the SPC literature have considered both multivariate and correlated observations (see for instance Lu and Reynolds, 1999; Montgomery and Mastrangelo, 1991; Woodall and Faltin, 1993), but this is a largely open area and needs to be further explored.

7. Conclusions and future research

In this paper, we describe a detailed quantitative procedure for monitoring and evaluating environmental performance. We show how an appropriate modification of existing statistical quality control techniques, in particular the CUSUM chart and corresponding process capability analysis, can be very useful for environmental process management and monitoring. We have discussed how this would work, using an extended example based on nitrate contamination data. Drawing on existing theory and based on the example, we suggest that CUSUM charts are valuable for emissions monitoring, as they tend to detect process shifts earlier than traditional IX–MR charts. The process capability analysis is particularly promising, as this gives decision-makers a concrete tool, to our knowledge for the first time, to assess the likelihood that their process will continue to comply with prevailing legislation. We have examined how process capability analysis is useful as a risk management tool for practitioners but also how it can benefit regulatory agencies.

Applying principles of statistical quality control to environmental management opens up many promising areas of research. First, one needs to continue to analyze and compare various types of charts, using emissions data rather than defect rates, to determine which design is appropriate for monitoring emissions. More extensive comparisons of traditional IX–MR charts with CUSUM and other charts should be performed. Second, we believe that emissions monitoring is a natural application of economic control charts, for which extensive theory exists but relatively little practical implementation. More theory and more practical guidelines on economic design of control charts, specifically for emissions monitoring, is called for. Third, better understanding of the precise form of regulatory requirements is needed: the appropriate control charts and process capability measures depend on whether emission rates may never exceed a certain limit or whether it is average emissions per unit time that are restricted, etc. We hope that this paper will provide the motivation for some of this work.

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