C-T-1: “Statistical Process Control I”

Nonparametric and Semiparametric Profile Monitoring by Nonlinear Mixed Effects Modeling

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Profile monitoring is an approach in quality control best used where the process data follow a profile (or curve). The majority of previous studies in profile monitoring focused on the parametric modeling of either linear or nonlinear profiles, with both fixed and random-effects, under the assumption of correct model specification. In many practical situations, the user has some knowledge of the nonlinear parametric form for a particular profile model. However, this model may be misspecified over a portion of the data or the relationship is too complicated to be described parametrically. Therefore, we propose two alternative approaches for nonlinear profile model, a nonparametric (NP) method and a semiparametric procedure that combines both parametric (P) and NP profile fits. We refer to our semiparametric procedure as nonlinear mixed robust profile monitoring (NMRPM). These two methods can account for the autocorrelation within profiles and treat the collection of profiles as a random sample from a common population. We adopt the usual Hotelling's (T^2) chart to check the unusual profiles. Simulation results show that our NP and NMRPM methods perform well in terms of providing adequate fits to the nonlinear profiles and in making decisions regarding outlying profiles when compared to a misspecified nonlinear mixed parametric model. In addition, however, the NMRPM method is robust to model misspecification because it also performs well when compared to a correctly specified nonlinear mixed parametric model. The proposed charts have good abilities to detect changes in Phase I data. We illustrate the proposed nonlinear mixed profile monitoring methods for two real applications, a bioassay dataset from DuPont Crop Protection and the vertical density profiles of particle boards.

A Bayesian SPC approach in modeling count type data

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We consider a process producing count type data from a Poisson distribution. The Poisson parameter (mean and variance) can experience jumps at random times. These jumps can be of either direction, i.e. either upward (causing worst process performance) or downward (process improvement) and of random size. Our interest is in detecting in an on-line fashion when the parameter exceeds certain prespecified thresholds. The methodology is based on a Bayesian sequentially updated scheme of mixture of Gamma distributions. Issues regarding inference and prediction will be mentioned. The developed methodology is very appealing for Phase I and/or short run count data.

A GLR Control Chart for Monitoring the Mean Vector of a Multivariate Normal Process

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A statistical process control (SPC) chart using the generalized likelihood ratio (GLR) statistic to monitor the mean vector of a multivariate normal (MN) process is discussed and its performance is evaluated. Performance comparisons to the Hotelling $\chi 2$ chart, multivariate exponentially weighted moving average (MEWMA) chart and the multi- MEWMA combination are carried out through computer simulations. Results show that the Hotelling $\chi 2$ chart and the MEWMA chart are only effective for a small range of shift sizes in the mean vector, while the GLR chart and some carefully designed multi-MEWMA combinations can give similarly better overall performance in detecting a wide range of shift magnitudes. Unlike most of these other options, the GLR chart does not require specification of tuning parameter value from the user. The GLR chart also has the advantage in process diagnostic: at the time of a signal, estimates of change-point and out-of-control mean vector are immediately available to the user. All these advantages of the GLR chart make it a favorable option for practitioners. For the design of the GLR chart, a series of easy to use equations are provided to users for calculating the approximated control limit to achieve any desired false alarm rate.

C-T-2: "Miscellaneous I"

Challenges in uncertainty quantification in nondestructive assay for nuclear safeguards

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Existing guides to express uncertainty in measurement partition errors into "random" and "systematic" components, and classify uncertainty evaluation options into "type A" and "type B." Type A evaluation uses observed data, while Type B evaluation uses other methods including expert judgment and assumed probability densities. Within the nuclear safeguards community, some nondestructive assay (NDA) methods invoke assumptions relating the source, intervening material, and detector response to the observed data (a "forward" model) in a manner that can result in "item-specific" bias. Some of the concepts recommended in existing guides such as the ISO GUM (guide to the expression of uncertainty in measurement) still apply. For example, the GUM describes error propagation in explicit algebraic forms relating observed/measured input quantities x_1, x_2, .., x_p to an estimate of the true value (measurand) y and also describes converting coverage intervals and assumed underlying probability distributions to error standard deviations. However, additional concepts are needed for NDA, perhaps in the form of a GUM+. We give two examples that give rise to the need for a GUM+. First, errors in predictors can require treatment using approaches that are more widely known in the statistics community. Second, uncertainty in the forward model relating source/ sample/detector to observed data should not be ignored.

Two Goodness-of-Fit Tests for Generalized Linear Mixed Models

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Generalized Linear Mixed Models (GLMMs) are extremely useful for modeling dependence among response variables inherent in longitudinal or repeated measures studies. However, using a misspecified GLMM can lead to poor statistical inference. We propose two candidate goodness-of-fit tests for the response distribution of a GLMM. The first is an extension to

GLMMs of the well known Chi-Square goodness-of-fit test. The second is based on a Cramer-von-Mises empirical distribution test. Power and size studies will be provided. We will attempt to fit a multinomial logistic model to a complex imaging dataset which aims to predict the progression of Alzheimer's disease among older adults. We will evaluate various GLMMs with these goodness-of-fit techniques.

Handy Sample Size Shortcuts for an Upper Confidence Bound on a Defect Rate

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We are often asked to provide a sample size to put an upper confidence bound on a defect rate. For example, "What sample size n must be free of defectives to be 95% confident the true defect rate is less than '1 in 10000'?". More generally, "How many n should be sampled and be free of defectives to be c% confident that the true defect rate is less and '1 in r'?" You may already know about the "rule of 3" for the 95% example, but it can be shown that there is a constant, dependent only on the confidence level 'c' that is multiplied by r to give the approximate n. This constant is cleverly derived using natural logs, and the formula is easy to remember. This presentation begins by showing the derivation of a rule for any confidence. Allowing 0 defectives gives a minimum n, but this is a very strict criterion so a few more constants are estimated to approximate n when 1 or 2 defectives are allowed. Finally there is an example of why you should anticipate additional defectives and plan ahead for them.

Since the client isn't always aware of just how daunting the request (i.e., "I want to be 99% confident the defect rate is less than one in a million!), keeping some of these shortcuts in your head allows you to compute 'ballpark' estimates on the spot, and you can appear smart and prepared before you formalize a more precise answer.

C-T-3: "Statistical Process Control II"

SPC: A student's perspective

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The purpose of this talk will be to take a quizzical look at some of the contradictions, inconsistencies and confusions surrounding the fundamental definitions and theories of Statistical Process Control, and demonstrate how these issues have a practical impact on the effectiveness of SPC. This reduction in effectiveness stems from the difficulty of trying to learn and use SPC. Over the years, the ideas and theories that SPC was premised upon have become convoluted, confusing, redundant and inefficient. It is for this reason that learning SPC and hence employing SPC effectively, is not such a straightforward task. For SPC to be effective it seems as though a universal set of ideas and nomenclature- which is currently absent from the field- need to be developed. In this talk I plan to demonstrate this necessity, and discuss some of the key concepts that should be addressed in such a coherent and universal language.

The Effect of Parameter Estimation on Upper-Sided Bernoulli CUSUM Charts

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The Bernoulli CUSUM chart has been shown to be effective for monitoring the rate of nonconforming items in high quality processes, where the in-control proportion of nonconforming items (p_0) is typically low. The implementation of the Bernoulli CUSUM chart is often based on the assumption that the in-control value p_0 is known; therefore, when p_0 is unknown, an accurate estimation is necessary. The low p_0 inherent to high quality processes implies that a very large, and often unrealistic, sample size may often be needed before enough nonconforming items are observed to accurately estimate p_0. We recommend using a Bayes estimator to approximate the value of p_0 in order to incorporate practitioner knowledge and avoid estimation issues when zero nonconforming items are observed. In this paper, we will investigate the effects of parameter estimation in Phase I on the upper-sided Bernoulli CUSUM chart. Especially when the prior distribution is accurately selected, the use of the Bayes estimator is shown to reduce the effects of estimation errors. This paper provides the first

investigation into the effects of estimation errors on the performance of the Bernoulli CUSUM chart, and further considers these effects with various sample sizes.

A Reconsideration of Geometric Charts with Estimated Control Limits

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The geometric control chart has been shown to be more effective than *p* and *np*-charts for monitoring the proportion of non-conforming items, especially for high quality processes. When implementing a geometric control chart, there are several practical issues that arise since the in-control proportion non-conforming is typically unknown and needs to be estimated. In this paper, we use the standard deviation of the average run length, SDARL, and the standard deviation of the average number of inspected items to signal, SDARL*, to show that much larger sample sizes (when compared to previous research) are needed in practice. The SDARL (or SDARL*) is used since practitioners would estimate the chart's control limits based on only one Phase I sample and therefore, it is important to recognize the effect of the variability of the ARL (or ARL*) on the chart's expected performance. In addition, we provide some insights on how to estimate the proportion non-conforming when zero nonconforming items are observed in the retrospective Phase I sample. The results of this paper will enable practitioners to have a better understanding of the statistical performance of geometric charts, based on estimated parameters, for both the in-control and out-of-control nonconforming proportions.

C-T-4: "Design of Experiments"

Response Surfaces, Blocking and Split Plots: An Industrial Experiment Case Study

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This case study highlights issues in design of experiments and analysis of which experimenters need to be aware. The particular experiment performed is more complex than standard experiments because it has response surface, blocking and split-plot elements which pose unique analysis challenges. The objective of the experiment was to determine appropriate levels of three factors to optimize two responses to ensure that the manufactured product meets customer requirements. This design has the desirable equivalent estimation property discussed in Vining et al. (2005). After discussing equivalent estimation designs, we illustrate portions of the analysis which are simplified as a result.

Using DOE with Tolerance Intervals to Verify Specifications

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Design of experiments followed by numeric and graphical optimization can be used to find a 'sweet spot'; i.e. an operating window. To ensure specifications are consistently met, uncertainty (variability) must be accounted for when defining boundaries of the operating window. We present a method of accounting for uncertainty using tolerance intervals. In general, larger sample sizes (DOEs) are required to control the width of tolerance intervals as compared to confidence intervals that are typically used to size designs. A two-factor tableting process is used to illustrate building and sizing a design to control the width of the tolerance intervals associated with specifications.

Application of a Six Variable Mixture Test Design (With a Non-Mixture variable)

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In this application a statistically designed experiment (DOE) was used to vary the six recipe variables simultaneously. However, the effect of each mixture component was assessed independently of other components. Previous to this application, product recipes were determined by a method of changing one-factor-at-a-time (OFAT method). This test design enabled measuring the interactions between the recipe variables, which could not have been done with the OFAT method of testing.

The test design consisted of 31 specially selected recipes being evaluated. The 31 recipes were specially selected to be representative of all possible recipes. Test products were made using each recipe. Each recipe was compared directly to a 'standard' recipe - the current recipe at that time. Over 70 quality measures, R&D product variables, and consumer response variables were analyzed on each product. Statistical data models were used to find the optimum product recipe.

A taste test using consumers was conducted to find their 'best recipe'. Candy consumers were asked to taste two products - a test recipe product and the standard product and indicate their preference. The consumer preference data was analyzed for each recipe when compared to the standard recipe. Statistical models were fitted to the data to find the consumer rating variability and to find the optimum recipe that also met quality and R&D standards.

The project results included discovering an optimum recipe that was superior to the current recipe used at that time. The conclusions were applied to ingredient recipes in three different world-wide best-selling candy products. The optimized recipe has been used successfully for many years.

This project showed that a statistically designed mixture experiment with a non-mixture component can be used to find an optimum product according to consumers.

The author acknowledges the contributions of Dr. George E. P. Box for his suggested statistical test design and his statistical analysis, particularly in the multi-response optimization phase to find the best recipe.

C-F-1: "Miscellaneous II"

Change-point Detection for Correlated Network Data

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To detect anomalous events in network traffic, standard change-point detection algorithms are challenged by the long-term correlations and non-stationarity in the stream of network counts. We employ a Generalized Linear Mixed Model (GLMM) to model the correlation structure with embedded random effects and to capture non-stationarity in the mean structure with fixed effects. The GLMM paradigm also allows the response variable, which is often counts, to be modeled directly. Using historical cycles of the data stream, the baseline GLMM model can be built to describe the data stream structure. We then predict future realizations of the random effects to be able to simulate potential sample paths for a future cycle. We detect changes in network performance by using a transformed CUSUM tracking statistic for which a control limit is found according to a desired false alarm rate. We illustrate the use of our proposed model with data from a real network and also conduct a simulation study to characterize its sensitivity to detect changes.

Methods for Monitoring Multiple Proportions When Inspecting Continuously

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As technology advances, the need for methods to monitor processes that produce readily available inspection data becomes essential. In this paper a multinomial CUSUM chart is proposed to monitor situations where items can be classified into more than two categories, there is no subgrouping of the items, and the direction of the out-of-control shift in the parameter vector can be specified. It is shown through examples that the multinomial CUSUM chart can detect shifts in category probabilities at least as quickly, and in most cases faster, than using multiple Bernoulli CUSUM charts. The properties of the multinomial CUSUM chart are determined through a Markov chain representation. If the direction of the out-of-control shift in the parameter vector cannot be specified, we recommend the use of multiple Bernoulli CUSUM charts.

Unsupervised Neutral Zone Classifiers

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Neutral zone classifiers are currently being used to allow for a region of neutrality when there is insufficient information to assign a specific predicted class with adequate confidence. The neutral zone classifier is derived by obtaining classification regions that trade off the cost of an incorrect classification against the cost of remaining neutral. We propose a new neutral zone classifier and show that it is equivalent to the Bayes classifier under certain conditions. Additionally, we demonstrate that our proposed classifier outperforms previous neutral zone classifiers in both expected cost of misclassification and computational complexity. The proposed neutral zone classifier is illustrated with a microbial community profiling application in which no training data is available. Previous implementations of neutral zone classification have only dealt with the scenario that training data exists. We perform the neutral zone classification in our example in an unsupervised setting using both parametric and nonparametric methods. In the parametric setting we assume that a power transformation exists such that the class distributions can be modeled as a mixture of normal distributions.