CONFERENCE GUIDE

XIIth INTERNATIONAL WORKSHOP on Intelligent Statistical Quality Control 2016

August 16-19, 2016

HELMUT SCHMIDT UNIVERSITÄT
Universität der Bundeswehr Hamburg

isqc 2016.hsu-hh.de

Introduction

It is already the XII$^{\text{th}}$ International Workshop on “Intelligent Statistical Quality Control” (ISQC 2016) following:

year	place
2013	Sydney, Australia
2010	Seattle, USA
2007	Beijing, China
2004	Warsaw, Poland
2001	Waterloo, Canada
1998	Würzburg, Germany
1995	Osaka, Japan
1990	Baton Rouge, USA
1986	Lyngby, Danmark
1983	Kent, UK
1980	Berlin, Germany

This time, it is hosted by the Helmut Schmidt University, the University of the Federal Armed Forces in Hamburg (HSU). We hope that it will be as successful as the previous ones. On the next pages of this booklet some useful information are collected.

Scientific program committee

Professor S. **Knoth**, Germany

Professor F. **Megahed**, U.S.A.

Professor Y. **Ojima**, Japan

Professor W. **Schmid**, Germany

Professor K.-L. **Tsui**, Hong Kong

Professor W. H. **Woodall**, U.S.A.

Hamburg, August 2016.

Miscellaneous

Workshop venue etc.

The workshop takes place in the Thomas Ellwein hall in the Mensa building of the HSU. Refreshments are served there too. Lunch is offered at the university canteen (in German: "Mensa") at the first floor of the same buidling.

Accessing the Internet

To access the internet during ISQC 2016 you can use the university's WiFi network. In your paperwork there is so called "Eventcamp Ticket" containing all the neccessary information.

- The net has SSID *event*.
- Connect to *event* using the credentials given on your ticket.
- For those sleeping on campus the code works in the guesthouse using a cable connection, too.

For those who have their machines configured to use *EDUroam*: Good news! It should just work!

If there are any problems don't hesitate to ask!

Some useful coordinates

- Local organizers:
  - Sven Knoth (room 1368, extension 3400[1], `knoth@hsu-hh.de`).
  - Doris Ehrich (room 2506, extension 3007, `doris.ehrich@hsu-hh.de`).
  - Detlef Steuer (room 1397, extension 2819, `steuer@hsu-hh.de`).
- Workshop URL: `http://isqc2016.hsu-hh.de`
- Address of University Campus: Holstenhofweg 85, 22043 Hamburg

  (for google maps, open street map etc.)
- Bus routes to/from Campus: 10, 263, 261, E62

  URL of public transport is `http://www.hvv.de`
- Restaurants ... waiting for registration responses.

[1]the full phone number would be then: +49 (0)40 6541 3400

Schedule

Tuesday, Aug 16

09:00 – 09:30	OPENING	
09:30 – 10:00	G Capizzi, G Masarotto *(U of Padua)*	Detecting Changes in the Basal Body Temperature
10:00 – 10:30	X Tang, FF Gan *(National U of Singapore)*	Risk-Adjusted Exponentially Weighted Moving Average Charting Procedure Based on Multi-Responses
10:30 – 11:00	BREAK	
11:00 – 11:30	E Epprecht, F Aparisi, O Ruiz *(PUC Rio de Janeiro, Valencia Tech, ESPOL Ecuador)*	The Variable Dimension Approach in Multivariate SPC
11:30 – 12:00	K Nishina, H Kawamura, K Okamato, T Takahashi *(Nagoya Tech)*	Monitoring and diagnosis of causal relationships among variables
12:00 – 12:30	E Yashchin *(IBM)*	Statistical Monitoring of Multi-Stage Processes
12:30 – 14:00	LUNCH	
14:00 – 14:30	E Collani *(U Würzburg)*	A Note on the Quality of Biomedical Statistics
14:30 – 15:00	T Alhwiti, F Megahed, M Weese, A Jones-Farmer *(Auburn U, Miami U)*	Mapping Research in Statistical Sciences: A Visual Exploration of 6,285 Publications (2000-2013) in the Journals of the American Statistical Association and their 92,000 Citations
15:00 – 15:30	T Suzuki, T Iwasawa, K Yoshida, N Sano *(Tokyo U of Science)*	Integrating Statistical and Machine Learning Approaches in Improving Inspection Process
15:30 – 16:00	BREAK	
16:00 – 16:30	K Tsui, Y Zhao *(CityU Hong Kong)*	Evolution of Big Data Analytics
16:30 – 17:00	E Saniga, D Davis, J Lucas *(U Delaware)*	A Primer on SPC and Web Data
17:00 – 17:30	W Woodall, M Zhao *(Virginia Tech)*	An Overview of Methods for Social Network Monitoring
19:00 – xx:xx	DINER AT BAR CELONA OR ...	

Wednesday, Aug 17

09:00 – 09:30	S Chakraborti *(U Alabama Tuscaloosa)*	Effects of Parameter Estimation on Control Charts
09:30 – 10:00	M Testik, C Weiß, Y Koca, O Testik *(Hacettepe U Ankara, HSU Hamburg)*	On the Phase I Shewhart Control Chart Limits for Minimizing Mean Squared Error When the Data are Contaminated
10:00 – 10:30	A Polunchenko *(U Binghamton)*	Optimal design of the Shiryaev-Roberts control chart: Give your Shiryaev-Roberts a headstart
10:30 – 11:00	Break	
11:00 – 11:30	T Lazariv, W Schmid *(EUV Viadrina Frankfurt O)*	Challenges in monitoring non-stationary time series
11:30 – 12:00	O Hryniewicz, K. Kaczmarek *(PAN Warsaw)*	Monitoring of short series of dependent observations using a control chart approach and data mining techniques
12:00 – 12:30	C Weiß *(HSU Hamburg)*	Control Charts for Time-Dependent Categorical Processes
12:30 – 14:00	Lunch	
14:00 – 14:30	Y Liu, JJ Zhu, D Lin *(PennState)*	A Generalized Likelihood Ratio Test for Monitoring Profile Data
14:30 – 15:00	D Montgomery, R Silvestrini *(Arizona State U, Rochester Tech)*	Design of Experiments: A Key to Successful Innovation
15:00 – 15:30	S Yasui, Y Ojima *(Tokyo U of Science)*	Optimal Designs of Unbalanced Nested Designs for Determination of Measurement Precision
18:00 – xx:xx	Diner at Feuerschiff or ...	

Thursday, Aug 18

09:00 – 09:30	TH Fan, YL Huang *(National Central U Taiwan)*	Bayesian Reliability Analysis of Accelerated Gamma Degradation Processes with Random Effect and Time-Scale Transformation
09:30 – 10:00	C Li, A Mukherjee, Q Su, M Xie *(Xi'an Jiaotong U, XLRI Jamshedpur, CityU Hong Kong)*	Statistical process monitoring of multivariate time-between-events data: Problems and possible solutions
10:00 – 10:30	W Yamamoto, L Jin *(U Electro-Communications Tokyo)*	A MGF Based Approximation to Cumulative Exposure Models
10:30 – 11:00	Break	
11:00 – 11:30	G Vining *(Virginia Tech)*	A Critique of Bayesian Approaches within Quality Improvement
11:30 – 12:00	J Bischoff, R Göb *(U Würzburg)*	Sampling plans in auditing
12:00 – 12:30	PT Wilrich *(FU Berlin)*	Sampling inspection by variables under Weibull distribution and Type I censoring
12:30 – 13:30	Lunch	
15:00 – xx:xx	Ship cruise or ...	

Friday, Aug 19

09:00 – 09:30	R Sparks, S Chakraborti *(CSIRO Sydney, U Alabama)*	Distribution Free Bivariate Monitoring of Dispersion
09:30 – 10:00	G Capizzi, G Masarotto *(U of Padua)*	Phase I Distribution-Free Analysis with the R Package dfphase1
10:00 – 10:30	S Knoth *(HSU Hamburg)*	New results for two-sided CUSUM-Shewhart control charts
10:30 – 11:00	Break	
11:00 – 11:30	M Morais, S Knoth *(I Superior Tecnico Lisboa, HSU Hamburg)*	On ARL-unbiased charts to monitor the traffic intensity of a single server queue
11:30 – 12:00	SF Yang, SW Lu *(National Chengchi U Taiwan)*	Loss Variation Monitoring Using An Optimal VSI Median Loss Control Chart
12:30 – 13:30	Lunch	
14:00 – xx:xx	E N D	

Abstracts

Detecting Changes in the Basal Body Temperature ➪

Giovanna Capizzi and Guido Masarotto

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During a normal menstrual cycle, the Basal Body Temperature (BBT) rises in the days following the ovulation. The shifts is small (on the average of 0.1°C); it can be abrupt or gradual and it typically persists almost until the end of the cycle. Detecting the onset of the BBT rise is an important problem in infertility man- agement, natural family planning and, also, in those medical studies using the day of the BBT rise as a proxy of the day of the ovulation. Traditionally either some simple run-rules or a CUSUM control chart have been used for detecting such a shift. How- ever, both these approaches do not account for the woman-to-woman variation and within-woman variation (i.e. for the variation cycle-to-cycle in the individual BBT distribution). Further, the existing procedures are not robust with respect to some phenomena, such as a fever attack producing outliers in the temperature measure- ments. In the talk, we will explore some more efficient solutions based on a more rigorous modeling of the BBT. Real data will be used to show some comparisons between the suggested procedure with some competing methods.

Risk-Adjusted Exponentially Weighted Moving Average Charting Procedure Based on Multi-Responses ➪

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Quality control charting procedures like cumulative sum (CUSUM) and exponentially weighted moving average (EWMA) charting procedures are traditionally used for monitoring the quality of manufactured products. Unlike a manufacturing process where the raw material is usually reasonably homogeneous, patients' risks of various surgical outcomes are usually quite different. The risks will have to be taken into consideration when monitoring surgical performances. Risk-adjusted CUSUM charting procedure for monitoring surgical performances has already been developed in the literature. In this paper, we develop a risk-adjusted EWMA charting procedure based on 2 or more outcomes. The properties of this procedure is studied. It is also compared with the risk-adjusted CUSUM procedure using a real surgical data set. Our study shows that the risk-adjusted EWMA procedure is an attractive alternative because of its performance and ease of interpretation.

The Variable Dimension Approach in Multivariate SPC ➪

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With multivariate processes, it may happen that some quality variables are more expensive and/or difficult to measure than the other ones, or they may demand much more time to measure. Their measurement may even be destructive. For monitoring such processes, the *variable dimension* approach was recently proposed. The idea is to measure always (at each sampling time) the "non-expensive" variables and to measure the expensive ones only when the values of the non-expensive variables give some level of evidence that the the process may be out of control. The procedure bears much similarity with the one of *variable parameters* (or *adaptive*) control charts, but differs in that it is not the sample size or sampling interval or control limits that are made dynamically variable, but rather the very variables being measured (thus the denomination "variable dimension"). We review and compare the several variants of the approach, the last one being an EWMA version. The approach may lead to significant savings in sampling costs (the savings depending, of course, on the ratio between the costs of measuring the "expensive" and the "inexpensive" variables). In many cases, the variable approach, contradicting the intuition, may also result in faster detection of special causes.

Monitoring and diagnosis of causal relationships among variables

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In statistical process control (SPC) there are two situations where monitoring multivariate is needed. One is that all of the variables monitored are product ones. The other is that the variables monitored are some product and process ones. In these cases, there are correlations among the variables. Therefore, application of multivariate control charts to such process control is useful.
In this paper, the latter case of monitoring causality is addressed. It is known that $T^2 - Q$ control charts, which are modified from standard multivariate control charts utilizing Mahalanobis distance, are an effective SPC tool. However, in using multivariate control charts, diagnosis is not so easy. The objective in this paper is to propose a diagnostic method for identifying an unusual causal relationship in a process causal model and then to examine its performance.
Our proposed method is to identify the nearest unusual model by utilizing the Mahalanobis distance between some supposed unusual models and the data indicating the out of control in Q charts.

Statistical Monitoring of Multi-Stage Processes

Emmanuel Yashchin

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In many complex processes, such as semiconductor manufacturing or production of mass storage systems, a large number of variables are monitored simultaneously. These variables can typically be impacted by several points of the manufacturing process, necessitating efforts that include not only monitoring but also diagnostics that includes establishing change-points, regimes and potential stages of influence. We discuss statistical methods used to handle such multi-stage data and give examples of applying these methods in large-scale monitoring systems.

A Note on the Quality of Biomedical Statistics

Elart von Collani

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During the last decades numerous articles were published dealing with the bad quality of biomedical statistics. However, most of the relevant papers confine themselves to describe misunderstandings, misinterpretations and misuses of statistical methods. In contrast, in this paper it is argued that the bad quality of biomedical statistics is also due to the statistical methodology and statistical methods themselves. This claim is illustrated by several examples. Special emphasize is laid on significance testing the most often applied statistical method in biostatistics. This paper aims at raising the awareness of the statistical community for what is going on in medicine and hoping that this will lead to improvements.

Mapping Research in Statistical Sciences: A Visual Exploration of 6,285 Publications (2000-2013) in the Journals of the American Statistical Association and their 92,000 Citations

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The size and scope of the literature on statistics can be overwhelming, which makes it difficult to identify emerging trends and see the relationships between different developments. Visualization techniques, coupled with statistical and data mining methods, have been found effective in achieving these goals in a number of application domains including healthcare and manufacturing research. In this paper, we apply these concepts to the field of statistical sciences. Our dataset is based on bibliographic information, including but not limited to authors, keywords, abstracts, citations, and funding information, extracted from 6285 papers published in the 17 journals of the American Statistical Association (ASA) in the period of 2000-2013. These bibliographic units of analyses allow us to address the following questions: a) What are the main research fields within statistics (based on a data-driven approach)? b) How do these research fields relate to each other? c) How do these fields develop over the time period from 2000-2013? And d) What are the main drivers for these publications? Our results indicate that using bibliometric visualization approaches can provide insights from analyzing the massive amounts of literature that has been published and cited by ASA papers over the past fourteen years.

Integrating Statistical and Machine Learning Approaches in Improving Inspection Process

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1. Introduction

Nowadays, many products are manufactured in larger quantities and at higher speed. Inspection processes also need to be operated at higher speed, without loss of accuracy at detecting nonconforming products. Regarding inspection of external appearances of the products, visual inspections have often been used in many processes, which many of them are now replaced by automatic inspections using sensors such as cameras. In this study, statistical tools and machine learning methods are applied to improve accuracy of an actual automatic inspection process.

2. Process and Data

The product taken up in this study is a cylindrical metal product. The external appearance is inspected automatically using the images taken by cameras installed in the process. The characteristics (RGB values) of the original images are converted into polar coordinates because the images are taken from above the product and the nonconforming defects tend to appear concentrically. This concept is shown in Fig.1. Regarding accuracy of the actual inspection process, the probability of type II error was

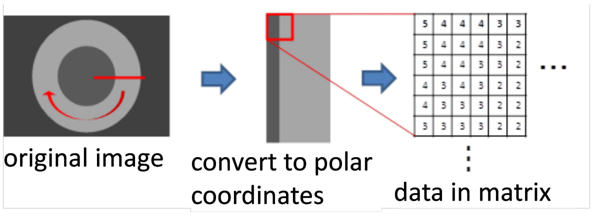

Fig. 1: Data used in analysis.

satisfactory but the probability of type I error needed improvement. In other words, sensitivity was satisfactory but specificity was not. Since there will be a need to detect nonconforming products which is more difficult to detect, the objective of the study is not limited to reduce type I errors but also reduce type II errors, in other words propose algorithms that improves overall accuracy of the inspection process.

3. Extracting features and creating variables

One of the most important parts of this study is to extract features from the original images and to create variables which will be used in later analyses. Many aspects of the images need to be accommodated such as; the first data of each row is next to the last data of the same row because the data are in polar coordinates, the position of the product changes slightly among them each time they are being imaged, etc. Some image processing techniques such as Gaussian filters and Laplacian filters are used. The data for each column are considered as waveform data so that techniques for time series analysis can be applied to extract the features. Quite a number of variables were created as candidates for future analyses.

4. Results

The methods used to identify the nonconforming products include both statistical and machine learning methods, namely discriminant analysis, MT system, neural networks, and support vector machines. Combination of the set of variables and identifying methods are applied to the trial data sets, which consist of intentional nonconforming defects that are harder to detect. Results showed improvement over the current algorithm.

5. Summary

Integrating statistical and machine learning approaches along with image processing techniques can be effective in improving algorithm in inspection process to detect nonconforming products.

Evolution of Big Data Analytics

Kwok Tsui and Yang Zhao

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Due to the advancement of computation power and data storage/collection technologies, the field of data modelling and applications have been evolving rapidly over the last two decades, with different buzz words as knowledge discovery in databases (KDD), data mining (DM), business analytics, big data analytic, etc. There are tremendous opportunities in interdisciplinary research and education in data science, system informatics, and big data analytics; as well as in complex systems optimization and management in various industries of finance, healthcare, transportation, and energy, etc. In this paper, we will present our views and experience in the evolution of big data analytics, challenges and opportunities, and some applications in system monitoring and management.

A Primer on SPC and Web Data

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In this paper we compare the website visitor data generated by a variety of commercially available analytics packages and discuss issues of data accuracy, consistency and unavailability of some important measures. We also discuss some common and perhaps new SPC methods for monitoring website effectiveness using this data.

An Overview of Methods for Social Network Monitoring

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In this paper we give an overview of statistical methods for the monitoring of social networks. We discuss the advantages and limitations of various methods as well as some relevant issues. Relationships are given between network monitoring methods and related monitoring methods in engineering statistics and public health surveillance. We evaluate the performance of a popular scan method for monitoring social networks. We encourage work in this area and give a number of research ideas.

Effects of Parameter Estimation on Control Charts

Subha Chakraborti

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Many control charts have been considered for process monitoring and control where the process parameters are specified or assumed known. When this is not the case, in practice, the unknown parameters are often estimated from retrospective data and the estimates are plugged-in to form the estimated control limits. It is known that estimating the control limits introduces practitioner to practitioner variability and degrades chart performance, in that nominal specifications such as the false alarm rate or the in-control average run-length are not met, unless there was a huge amount of data.

To meet these challenges, a recent proposal has been to study the conditional run-length distribution and some associated performance characteristics. In this context, we consider a general framework for various univariate control charts, both normal theory and nonparametric, under which effects of parameter estimation can be examined. Examples are provided.

On the Phase I Shewhart Control Chart Limits for Minimizing Mean Squared Error When the Data are Contaminated ➪

Murat Caner Testik, Christian H. Weiß, Yesim Koca, Ozlem Muge Testik

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A Shewhart-type control statistic lacks memory of previous observations on a monitored quality characteristic. Therefore, Shewhart-type control charts are known to be relatively insensitive to moderate-to-small sized shifts in the process parameters. Yet, these charts are recommended in the literature for the design stage of a control chart, namely Phase I, where unknown process parameters are estimated and the control limits are set for online process monitoring in Phase II. There are several studies that considered time-weighted control charts for the Phase I application, as well as alternative estimators, to improve the dign for monitoring in Phase II. Some studies also considered the design of Shewhart control charts based on false alarm rates or overall false alarm probabilities, where it is concluded that the control limits may be widened. In this study, we simulate assignable causes of variation by contaminating sets of Phase I observations and investigate the use of traditional Shewhart control chart for parameter estimation when the observations are normally distributed. By varying the distance of the control limits from the center-line, Phase I Shewhart control charts are evaluated in terms of the true and false alarm percentages, number of iterations performed to finalize the Phase I analysis, and the mean squared error of the parameter estimates. Some practical recommendations are provided.

Optimal Design of the Shiryaev-Roberts Chart: Give Your Shiryaev-Roberts a Headstart ➪

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We offer a numerical study of the effect of headstarting on the performance of a Shiryaev–Roberts (SR) chart set up to control the mean of a normal process. The study is a natural extension of that previously carried out by Lucas and Crosier (1982) for the CUSUM scheme. The Fast Initial Response (FIR) feature exhibited by a headstarted CUSUM turns out to be also characteristic of an SR chart (re-)started off a positive initial score. However, our main result is the observation that a FIR SR with a carefully designed *optimal* headstart is not just faster to react to an initial out-of-control situation, it is nearly *the* fastest *uniformly*, i.e., assuming the process under surveillance is equally likely to go out of control effective any sample number. We explain the optimization strategy, and tabulate the optimal initial score, control limit, and the corresponding "worst possible" out-of-control Average Run Length (ARL), considering mean-shifts of diverse magnitudes and a wide range of levels of the in-control ARL.

References

1. Lucas JM and Crosier RB (1982). Fast initial response for CUSUM quality-control schemes: Give your CUSUM a head start. *Technometrics* **24**(3), 199-205.

Challenges in monitoring non-stationary time series ➪

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Usually, in the literature on Statistical Process Control for time correlated data it is assumed that the underlying process is stationary. However, in applications such an assumption may not always hold. In finance or in economics we are often faced with situations where the process is close to non-stationarity or even non-stationary. The existing techniques may fail while monitoring such processes. Therefore, it is important to have tools that can correctly detect changes in non-stationary processes. However, monitoring of non-stationary processes has not yet received much consideration. Lazariv and Schmid (2015) used state-space models for modelling the underlying process. These processes are very flexible and allow the modelling of non-stationary processes. In the current paper we want to discuss the problems and challenges one faced, when attempting to monitor a non-stationary process. First, we introduce a literature overview of the subject. Second, we compare the control charts of Lazariv and Schmid (2015) with the classical tools used in multivariate process control (e.g., multivariate modifications of the Exponentially-Weighted Moving Average (MEWMA) control chart and the cumulative sums (MCUSUM) chart). We answer the question, how the performance of these schemes changes under non-stationarity conditions. Finally, we provide an extensive com- parison study, where we compare all control charts and discuss the choice of a suitable performance measure.

References

1. Lazariv T. and Schmid W.: Surveillance of non-stationary processes. Submitted for publication, 2015.
2. Frisén, M.: Statistical surveillance. Optimality and methods. *International Statistical Review* **71**(2), 403-434, 2013.

Monitoring of short series of dependent observations using a control chart approach and data mining techniques ➪

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Many different control charts have been proposed during the last 30 years for monitoring of processes with autocorrelated observations (measurements). The majority of them are developed for monitoring residuals, i.e., differences between the observed and predicted values of the monitored process. Unfortunately, statistical properties of these chart are very sensitive to the accuracy of the estimated model of the underlying process. In this paper we consider the case when the information from the available

data is not sufficient for good estimation of the model. Therefore, we use the Bayesian concept of model averaging in order to improve model prediction. The novelty of the proposed method consists in the usage of computational intelligence methodology for the construction of alternative models and the calculation of their prior probabilities (weights).

Control Charts for Time-Dependent Categorical Processes ➪

Christian Weiß

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The monitoring of categorical processes received increasing research interest during the last years, but usually on the premise of the underlying process being serially independent. We start with a brief survey of approaches for modeling and analyzing serially dependent categorical processes. Then we consider two general strategies for monitoring a categorical process: If the process evolves too fast to be monitored continuously, then segments are taken in larger intervals and a corresponding statistic is plotted on a control chart; here, one has to carefully consider the serial dependence within the sample. If a continuous process monitoring is possible, then the serial dependence between the plotted statistics has to be taken into account. For both scenarios, we propose appropriate control charts and investigate their performance through simulations.

Recent Advances in Design of Computer Experiments ➪

Yang Liu, JunJia Zhu, Dennis K. J. Lin

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Profile data emerges when the quality of a product or process is characterized by a functional relationship among (input and output) variables. In this paper, it is assumed that each profile has one response variable Y, one explanatory variable x, and the functional relationship between these two variables can be rather arbitrary. We propose a general method based on the Generalized Likelihood Ratio Test (GLRT) to perform Phase II monitoring of profile data. Unlike existing methods in profile monitoring area, the proposed method uses nonparametric regression to estimate the on-line profiles and thus does not require any functional form for the profiles. Both Shewhart-type and EWMA-type control charts are considered. The average run length (ARL) performance of the proposed method is studied by using a nonlinear profile dataset. It is shown that the proposed GLRT-based control chart can efficiently detect both location and dispersion shifts of the on-line profiles from the baseline profile. An upper control limit (UCL) corresponding to a desired in-control ARL value is constructed.

Design of Experiments: A Key to Successful Innovation ➪

Douglas C. Montgomery and Rachel T. Silvestrini

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Does the use of statistical methodology such as design of experiments stifle innovation? This is an important theme in this paper. Design of experiments is viewed as part of a process for enabling both breakthrough innovation and incremental innovation, without which western society will fail to be competitive. Quality engineering technology in general is part of a broader approach to innovation and business improvement called statistical engineering. The most powerful statistical technique in statistical engineering is design of experiments. Several important developments in this field are reviewed, the role of designed experiments in innovation examined, and new developments and applications of the methods discussed.

Optimal Designs of Unbalanced Nested Designs for Determination of Measurement Precision ➩

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Precision of measurement results can be recognized as variance components of random effect models. The variance components are estimated from measurement results that are taken by conducting a collaborative assessment experiment. The measurement results follow a statistical model of a nested design. Although balanced nested designs are widely used, staggered nested designs, which are one of unbalanced nested designs, have the statistical advantage that degrees of freedom in all stages except for the top stage are equal. Thus, the balanced nested designs do not necessarily have the better performance from the statistical viewpoints. In this study, the D-optimal designs are identified in the general nested designs, which including both balanced and unbalanced ones, with considering the practical feasibility of collaborative assessment experiments as well.

Bayesian Reliability Analysis of Accelerated Gamma Degradation Processes with Random Effects and Time-scale Transformation ➩

Tsai-Hung Fan, Ya-Ling Huang

National Central U Taiwan, thfanncu@gmail.com, erin98102@gmail.com

Accelerated degradation tests have been widely used to assess the lifetime information of highly reliable products. In this work, we apply Bayesian approach to the accelerated degradation test with log linear link function in the stress level of the acceleration factor. The model is based on random effects gamma processes with time-scale transformation. A mixture prior is considered to identify the parameter of time-scale transformation. Reliability inference of the failure time distribution under normal use condition will be described through the posterior sample of the underlying parameters obtained by the MCMC procedure. Simulation study is presented to evaluate the performance of the proposed method, and discuss model fitting issue regarding the random effects and fixed effect gamma process models via DIC model selection criteria. The proposed method is applied to the LED light intensity data as well.

Statistical process monitoring of multivariate time-between-events data: Problems and possible solutions ➩

Chenglong Li, Amitava Mukherjee, Qin Su, Min Xie

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In the recent years, a lot of attention is paid to univariate monitoring of time-between-events. When the univariate problem is extended to a multivariate situation, this study indicates that there is an emerging issue about the presence of asynchronous observations. This brings the new statistical challenge due to the way of data acquisition changes. This study also tries to give some possible solving ideas for the monitoring and analysis of multivariate TBE data streams.

A MGF Based Approximation to Cumulative Exposure Models

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Online monitoring data contains various measurements of the activity of the system. The amounts of works are also measured in various ways. When we model the reliability of a system, the intensity or the risk of failure events, we need to choose a time scale. Though there should be genuine time scales for each failure phenomenon, the field data including online monitoring data may not be able to provide evidence for them. There are many uncontrollable factors in the field. Many variables are monotone increasing and highly correlated with each other within a system. Yet they also represent the differences among systems. This article tries to build a bridge between two useful approaches, alternative time scale (Kordonsky and Gertsbakh, 1997, Duchesne and Lawless, 2002) and cumulative exposure model (Hong and Meeker, 2013), by assuming the stationarity of of the increments of these measurements within a system.

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A Critique of Bayesian Approaches within Quality Improvement

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Bayesian approaches are increasingly popular within the statistics community. However, they currently do not seem to find wide application within the industrial statistics/quality improvement community. This talk examines some of the basic reasons why.

This talk begins by reviewing Deming's concepts of analytic versus enumerative studies. It also discusses the importance of the scientific method within quality improvement.

Together, these concepts provide a framework for evaluating when Bayesian approaches make good sense, where they make little sense, and where they fall somewhere in between. This paper touches on statistical sampling plans, statistical process monitoring, and the design and analysis of experiments.

Sampling plans in auditing

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The European Commission Audit Directive of 17 May 2006 enforces the use of the International Standards on Auditing (ISA) for all Statutory audit to be performed in the European Union. The standard ISA 500 "Audit Evidence" declares the practice of non-statistical judgmental sampling to be inadequate. By ISA 500, statistical sampling becomes mandatory in audit sampling. The audit sampling standard ISA 530 is of conceptual nature and provides no methodological and technical advice for audit sampling practice. The following characteristics are essential for audit sampling schemes: 1) Account for prior knowledge on population parameters, 2) control both the risk of erroneous acceptance and the risk of erroneous rejection, 3) enable both decisions and estimation of population parameters. The classical ISO acceptance sampling do not conform to these requirements. We outline the plan for an auditing attributes sampling standard and the underlying methodology.

Sampling inspection by variables under Weibull distribution and Type I censoring

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The lifetime (time to failure) of a product is modelled as Weibull distributed (with unknown parameters); in this case the logarithms of the lifetimes are Gumbel distributed. Lots of items shall be accepted if their fraction p of nonconforming items (items the lifetime of which is smaller than a lower specification limit t_L) is not larger than a specified acceptable quality limit. The acceptance decision is based on the $r \leq n$ observed lifetimes of a sample of size n which is put under test until a defined censoring time t_C is reached (Type I censoring). A lot is accepted if $r = 0$ or $r = 1$ or if the test statistic $y = \hat{\mu} - k\hat{\sigma}$ is not smaller than the logarithm of the specification limit, $x_L = \log(t_L)$, where k is an accepance factor and $\hat{\mu}$ and $\hat{\sigma}$ are the Maximum Likelihood estimates of the parameters of the Gumbel distribution. The parameters of the sampling plan (acceptance factor k, sample size n and censoring time t_C) are derived so that lots with $p \leq p_1$ shall be accepted with probability not smaller than $1 - \alpha$. On the other hand, lots with fractions nonconforming larger than a specified value p_2 shall be accepted with probability not larger than β. n and t_C are not obtained separately but as a function that relates the sample size n to the censoring time t_C. Of course, n decreases if the censoring time t_C is increased. For $t_C \to \infty$ the smallest sample size, i.e. that of the uncensored sample, is obtained. Unfortunately, the parameters of the sampling plan do not only depend on the two specified points of the OC, $P_1(p_1, 1 - \alpha)$ and $P_2(p_2, \beta)$, but directly on the parameters τ and δ of the underlying Weibull distribution or equivalently, on the parameters $\mu = \log(\tau)$ and $\sigma = 1/\delta$ of the corresponding

Gumbel distribution. Since these parameters are unknown we assume that the hazard rate of the underlying Weibull distribution is nondecreasing ($\delta \geq 1$). For the design of the sampling plan we use the limiting case $\delta = 1$ or $\sigma = 1/\delta = 1$. A simulation study shows that the OC of the sampling plan is almost independent of σ if the censoring time t_C is not smaller than the specification limit t_L.

Distribution Free Bivariate Monitoring of Dispersion ➪

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Non-parametric charts are growing in popularity in the literature because control measures often have asymmetric distributions and are multivariate in nature. In particular, monitoring environmental risk often involves assessing the risk involving several measures such as e-coli, chlorophyll-a, nutrient loads, faecal coliforms, turbidity etc which are all positive right-skewed distributed. Often the log-normal distribution is assumed for these measures as a matter of convenience typically because no other realistic options are available in the literature. In most cases the log-normal distribution is inappropriate.

This paper therefore focuses on evaluating practical approaches to monitoring the dispersion parameter for a wide range of positively distributed variables in bivariate situations. Typical approaches to monitoring the dispersion for univariate cases skew data is to first finding the “best” Box-Cox transformation of the data to normality and then apply the S-chart to the transformed data. This approach is can been extended to the multivariate normal distribution. This paper recommends a distribution free approach appropriate for bivariate data based on data depth and robust regression. This paper compares these new distribution free approaches in a simulation study. These comparisons are made for a wide range of asymmetric distributions. The paper plans to provide good practical advice to those monitoring the dispersion for bivariate asymmetric variables.

Phase I Distribution-Free Analysis with the R Package dfphase1 ➪

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Phase I distribution-free methods have received an increasing attention in the recent statistical process monitoring literature. Indeed, violations of distributional assumptions may largely degrade the performance and sensitivity of parametric Phase I methods. For example, the real false alarm probability, i.e., the probability to declare unstable a process that is actually stable, may be substantially larger than the desired value. Thus, several researchers recommend to test the shape of the underlying IC distribution *only after* process stability has been established using a distribution-free control chart. In the paper, we describe the R package `dfphase1` which provides an implementation of many of recently suggested Phase I distribution-free methods. Indeed, becouse of the relatively high computational complexity of some of these methods, we believe that their diffusion can be helpfully encouraged supporting practitioners with an easy-to-use dedicated software. The use of the package is illustrated with real data from an oil refinery.

New results for two-sided CUSUM-Shewhart control charts ➪

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Already Yashchin (1985), and of course Lucas (1982), studied CUSUM chart supplemented by Shewhart limits. Interestingly, Yashchin (1985) proposed to calibrate the detecting scheme via $P_\infty(RL > K) \geq 1-\alpha$ for the run length (stopping time) RL in the in-control case. Calculating the RL distribution or related quantities such as the ARL are slightly complicated numerical tasks. Similarly to Capizzi & Masarotto (2010) we deploy less common numerical techniques (Clenshaw-Curtis quadrature, collocation) to determine the ARL and other RL based measures. Note that the two-sided CUSUM chart consisting of two one-sided charts leads to a more demanding numerical problem than the single two-sided EWMA chart.

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On ARL-unbiased charts to monitor the traffic intensity of a single server queue ➪

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We know too well that the effective operation of a queueing system requires maintaining the traffic intensity ρ at a target value ρ_0. This important measure of congestion can be monitored by using control charts, such as the one found in the seminal work by [1] or more recently in [2]. For all intents and purposes, this paper focus on three control statistics chosen by [3] for their simplicity, recursive and Markovian character:

- X_n, the number of customers left behind in the $M/G/1$ system by the n^{th} departing customer;
- $\hat{X}_n$, the number of customers seen in the $GI/M/1$ system by the n^{th} arriving customer;
- W_n, the waiting time of the n^{th} arriving customer to the $GI/G/1$ system.

Since an upward and a downward shift in ρ are associated with a deterioration and an improvement (respectively) of the quality of service, the timely detection of these changes is an imperative requirement, hence, begging for the use of ARL-unbiased charts [4] in the sense that they detect any shifts in the traffic intensity sooner than they trigger a false alarm.

In this paper, we focus on the design of these type of charts for the traffic intensity of the three single server queues mentioned above.

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A Median Loss Control Chart

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The quality and loss of products are crucial factors separating competitive companies in many industries. Firms widely employ a loss function to measure the loss caused by a deviation of the quality variable from the target value. Monitoring this deviation from the process target value is important from the view of Taguchi's philosophy. In reality, the distribution of the quality variable may be skewed and not normal, and the in-control process mean may not be the target. We propose a median loss control chart to detect the changes in the process loss center or equivalently the shifts in the process deviation from the mean and target and/or variance for the quality variable with a skewed distribution. We also derive the median loss control chart with variable sampling intervals to detect small shifts in the process loss center. The out-of-control detection performance of the proposed median loss control chart and the median loss chart with variable sampling intervals are illustrated and compared for the process variable with a left-skewed, symmetric or right-skewed distribution. Numerical results show that the median loss chart with variable sampling intervals performs better than the median loss chart in detecting small to moderate shifts in the process loss center or in the difference of mean and target and/or variance of a process variable. The median loss chart and the median loss chart with variable sampling intervals also illustrate the best performance in detection out-of-control process for a process quality variable with a left-skewed distribution.

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