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Capaci, Francesca; Vanhatalo, Erik; Bergquist, Bjarne; Kulahci, Murat

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Managerial implications for improving continuous production processes

Francesca Capaci (francesca.capaci@ltu.se)
Luleå University of Technology, Luleå, Sweden

Erik Vanhatalo
Luleå University of Technology, Luleå, Sweden

Bjarne Bergquist
Luleå University of Technology, Luleå, Sweden

Murat Kulahci
Luleå University of Technology, Luleå, Sweden and
Technical University of Denmark, Kongens Lyngby, Denmark

Abstract

Data analytics remains essential for process improvement and optimization. Statistical process control and design of experiments are among the most powerful process and product improvement methods available. However, continuous process environments challenge the application of these methods. In this article we highlight SPC and DoE implementation challenges described in the literature for managers, researchers and practitioners interested in continuous production process improvement. The results may help managers support the implementation of these methods and make researchers and practitioners aware of methodological challenges in continuous process environments.

Keywords: Productivity, Statistical tools, Continuous processes

Introduction

Continuous production processes (CPPs), often found in, e.g., pulp and paper, chemical, steel, or other process industries, constitute a significant part of goods production. In a CPP, the product is gradually and often with minimal interruption refined through different process steps (Dennis and Meredith, 2000). Raw materials in these processes often stem directly from natural resources and characteristics of inputs such as ores or wood will therefore vary substantially. CPPs are often large-scale and tend to include interconnected process steps and complex flows. Continuous production environments are typically inflexible producing only one or a few products, require large investments, and occupy a large area. Wear and varying raw material characteristics are examples of frequent disturbances, making engineering process control (EPC) necessary to stabilize product quality and process characteristics (Montgomery et al., 1994; Box and Luceño, 1997). Although EPC keeps quality characteristics on target, CPPs require continuous improvements to remain competitive (Hild et al., 2001).

The main possibilities to learn and improve any process come from the analysis of observational and experimental process data. While first principles can be supported by correlations among observational data, experiments are usually needed to discover causal relationships in industrial processes (Montgomery, 2012).

In this article, we focus on statistical process control (SPC) and design of experiments (DoE) since they constitute two fundamental process improvement methodologies. The purpose of SPC is to monitor the process and reduce process variation through identification and elimination of assignable causes of variation. In the SPC field univariate and multivariate control charts constitute the most important improvement tools. Alarms issued by control charts indicate the presence of potential assignable causes (i.e., unusual events). Root-cause analysis is the next step to uncover reasons for these events and if possible, to eliminate their causes. SPC is a long-term improvement methodology, while EPC is a short-term control strategy that transfers variability from the controlled variable to manipulated variables (MacGregor and Harris, 1990). The purpose of DoE is to plan, conduct and analyse experiments to improve products and processes in a systematic and statistically sound manner.

Since their introduction in the early twentieth century, management controlled improvement programs such as Robust Design, Total Quality Management, and Six Sigma have been promoting these methodologies. Their apparent omission from the currently popular lean program descriptions, as well as methods within popular data analytics and machine learning, indicate that textbook implementation of these methods may be ill-suited for today's production environment. It is becoming increasingly apparent that standard SPC and DoE methods need to be adapted to challenges such as rapid data collection from multiple and interconnected sources and massive datasets (Vining et al., 2015), which are common for CPPs. We argue that DoE and SPC are far from obsolete and that companies will not take full advantage of the big data transition without such proper statistically based methodologies for learning and improvements. However, practitioners must be aware of the challenges that this data rich environment brings to SPC and DoE.

McAfee et al. (2012) highlight leadership and decision-making as important management challenges in the big data era. If managers of CPPs understand SPC and DOE challenges, they can support pairing their data with effective improvement methods. Hild et al. (1999) suggests using thought maps to promote improvement methods and critical thinking. While managers need to be aware of techniques such as DoE and SPC to reduce resources, to meet customer requirements and, perhaps most important, they should also promote their use (Lendrem et al., 2001; Bergquist and Albing, 2006; Tanco et al., 2010).

The purpose of this article is to highlight challenges and development needs described in the literature for SPC and DoE in CPPs. We also provide some examples of state-of-the-art solutions to current challenges.

Method

Literature searches were conducted in April 2017 using the Scopus database, limited to publications in English in the last 30 years (1987->). Table 2 and 3 show sequential search steps and keywords used. We examined reference lists of selected publications in Search 4 to minimize the risk of missing relevant publications, following recommendation by Randolph (2009).

Table 2 – Search terms and number of publications in each step in the SPC search.

Search #	*Search terms and queries*	*Step 1*	*Step 2*	*Step 3*	*Step 4*	*Step 5*
Search 1	(“statistical process control”) *AND* (“continuous process” *OR* “continuous production”)	136	32	14	Classification	23 (7)
Search 2	(“statistical process monitoring”) *AND* (“continuous process” *OR* “continuous production”)	16	2	0		
Search 3	(“statistical process monitoring”) *AND* (“process industry”)	9	4	3		
Search 4	References of selected publications in Search 1, 2 and 3	436	64	35		

The initial sample from Step 1 is the number of publications found using the keywords in Scopus. Duplicates were deleted in each search. In Step 2, the initial sample was reduced by screening titles, author keywords, and sources. Conference articles were excluded if a later journal article of the same authors and with the same title was found. Many publications were rejected after abstracts were read in Step 3. We then classified challenges or development needs for DoE and SPC in CPPs in Step 4. Publications were further analysed in Step 5 to identify the central or pivotal publications on which our results are mainly based. Additional relevant publications known by the authors (indicated in brackets at Step 5 in Tables 2 and 3) were also added and analysed.

Table 3 – Search terms and number of publications in each step in the DoE search.

Search #	*Search terms and queries*	*Step 1*	*Step 2*	*Step 3*	*Step 4*	*Step 5*
Search 1	(“design of experiments”) *AND* (“continuous process” *OR* “continuous production”)	49	27	8	Classification	20 (11)
Search 2	(“experimental design”) *AND* (“continuous process” *OR* “continuous production”)	50	25	15		
Search 3	(“experimental design”) AND (“process industry”)	12	7	2		
Search 4	References of selected publications in Search 1, 2 and 3	877	66	40		

SPC challenges in continuous production processes

The literature review revealed many technical solutions to challenges arising when using SPC in continuous processes. The aim of this section is to provide an overview of challenges and potential strategies that managers can promote. Technical details are therefore not be completely covered in this article.

Process transitions and data acquisition

Operating conditions frequently change due to grade changes, restarts or process adjustments and process inertia leads to transition phases. Data storage should be designed as to preserve the history of transitions phases and interrelation of process variables during transitions (Kourti, 2003). Process transitions may involve loss of production time and increased costs due to produced sub-grade products. The monitoring phase in SPC should begin after the transition is complete (Duchesne et al., 2002). Moreover, properly stored historical data is crucial to gain process knowledge.

Multivariate nature of process data

Important reactions such as phase changes from ore to metal are difficult to measure accurately. Instead, engineers try to measure a multitude of secondary variables such as temperatures and pressures as proxies to the real, hidden process events. Technological development continuously reduces sensor costs and increases data storage capacity. Today measuring, e.g., a reactor temperature at multiple locations is easily achieved. With many underlying phenomena, the analyst soon has hundreds of cross-correlated variables that need simultaneous monitoring. A univariate approach with each variable in separate control charts is inefficient and often misleading. Fortunately, there are many multivariate SPC tools available (see, e.g., Shi and MacGregor, 2000; Qin, 2012, and Ge et al., 2013). These methods can be classified in five categories: *Gaussian process monitoring methods* (e.g. latent structure variable methods), *non-Gaussian process monitoring methods* (e.g. independent component analysis), *non-linear process monitoring methods* (e.g. neural networks), *time varying and multimode process monitoring* (e.g. adaptive/recursive methods) and, *dynamic process monitoring* (e.g. dynamic multivariate SPC methods). The choice of multivariate SPC method depends on assumed process characteristics: Gaussian/non-Gaussian, static/dynamic and, linear/non-linear. Data characteristics such as if data are two or multidimensional or if data can be assumed to be time independent also affect the choice. Multivariate monitoring based on latent variables such as Principal Component Analysis (PCA) and Partial Least Square (PLS) are popular and important especially due to their dimensionality reduction properties (Frank and Friedman, 1993; MacGregor and Kourti, 1995). Kourti et al. (1996) provide a review of examples with industrial applications of latent variable monitoring techniques in process plants such as a chemical smelter, a polymerization process, a pulp digester, and many others. Ferrer (2014) illustrates how latent variable methods for process understanding, monitoring and improvement can be used effectively in a petrochemical CPP. Latent variable techniques use the process variables' cross-correlation. Process monitoring uses a few linear combinations of the process variables (the so-called latent variables). Commonly, a Hotelling T^2 control chart simultaneously monitors the retained latent variables from the PCA/PLS model whereas the squared prediction error (Q) chart monitors the model's residuals. When the charts signal an out-of-control observation, these composite statistics are often decomposed into the original variables for fault identification (Himes et al., 1994; Ku et al., 1995; Kourti and MacGregor, 1996; Yoon and MacGregor, 2001; De Ketelaere et al., 2015)

Serial correlation (autocorrelation)

Process variables in CPPs are often highly (and positively) autocorrelated due to high sampling rates and process dynamics. This challenge is increasing due to sensor development and availability of almost unlimited data storages. Serial correlation usually means that the current observation is similar to the previous one. Since autocorrelation affects the estimation of the process' variability, autocorrelation can lead to increased false alarm rates in both univariate and multivariate control charts or incorrectly estimated process capability indices (Tracy et al., 1992; Runger, 1996; Mastrangelo et al., 1996; Bisgaard and Kulahci, 2005; Jarrett and Pan, 2007).

Two ways to handle SPC of multivariate, autocorrelated data have been suggested. The first employs a standard univariate or multivariate control chart but with adjusted control limits to achieve the desired in-control alarm rate. The second requires 'filtering out the autocorrelation' through a univariate or multivariate time series model and applying a control chart to the residuals from this model. However, fitting a multivariate time series model with many variables is difficult.

Latent variables based SPC is recommended for cases with multiple and highly cross-correlated process variables. Vanhatalo and Kulahci (2015) show that autocorrelated process variables still affect the monitoring performance of PCA based control charts since the principal components also are autocorrelated. Control charts based on PCA/PLS are well equipped to deal with cross-correlated, independent and, stationary data but will be affected by autocorrelation. De Ketelaere et al. (2015) review extended versions of PCA/PLS based monitoring methods available for more complex process and data characteristics, see Figure 1. Specifically, dynamic PCA/PLS have been promoted for handling the autocorrelation by adding time-lagged variables (Ku et al., 1995) aiming to transform autocorrelation into cross-correlation that is suitable for PCA/PLS.

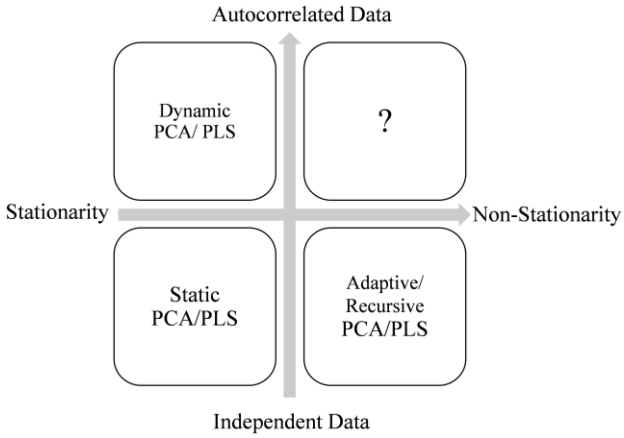

Figure 1 – Process and data challenges and available PCA/PLS methods.

Process capability analyses are important and popular for assessing process performance, frequently used in six sigma companies and promoted by various management and industrial systems standards. However, positive autocorrelation would lead to an overestimation of process capability indices (Shore, 1997; Zhang, 1998; Sun et al., 2010; Lundkvist et al., 2012).

The literature seems to lack a comprehensive solution to assessing process capability from processes with autocorrelated and multivariate data. Pan and Huang (2015) develop two multivariate process capability indices for autocorrelated data and compare their performance via a simulation study and, Mignoti and Oliveira (2011) propose an adjustment of multivariate capability indices to handle autocorrelation.

Presence of engineering process control

Fault detection using SPC control charts could fail when EPC is applied. Integrating SPC and EPC requires applying control charts to manipulated and not to controlled process variables. Box and Kramer (1992) provide a comprehensive discussion on the interface between EPC and SPC and Montgomery et al. (1994) demonstrate the effectiveness of integrating SPC and EPC in process surveillance. Contributions related to this challenge for most CPPs can also be found in Box and Luceño (1997), Janakiram and Keats (1998), Capilla et al. (1999), Tsung (2000) and in Huang and Lin (2002).

DoE challenges in continuous production processes

The literature seems unanimous on the benefits of using DoE but also on the need of managerial support for increased use of DoE in industry (Tanco et al., 2009; Bergquist, 2015b). In this section, we describe specific challenges when applying DoE in CPPs but also suggest remedies.

Large scale and costly experimentation

Operations in CPP plants typically occur around the clock with few operators in charge. Full-scale experiments may thus involve the majority of the production staff, making managerial support, coordination, and information flow essential. Moreover, the often lengthy experimental campaigns can jeopardize the production plan. Previously unexplored factor settings may lead to production of low-grade products. Time and costs are therefore unavoidable constraints. Nevertheless, the need for improvements often make experimentation necessary. Relevant examples include Wormbs et al (2004) who describe experimentation to evaluate production methods of milk using a three factors, two-levels full factorial design in a dairy company and, Gonnissen et al. (2008) who show how a continuously produced powder mixture can be optimized using DoE.

We have found two best practices that managers can promote: (i) support and allocate resources to the planning phase of the experiment and (ii) create awareness of experimental strategies suitable for large scale experimentation.

Montgomery (2012) and Box et al. (2005) highlight the planning activities preceding the actual experiments. However, recognizing that the planning phase is seldom a taught skill, Coleman and Montgomery (1993) provide a systematic approach to plan an industrial experiment. Later, Vanhatalo and Bergquist (2007) adapt this approach to CPPs. Beside a well-chosen design, the planning phase should include, e.g., a clear problem statement, background such as expert knowledge or previous experiments, and someone responsible for coordination and information flow. Of special importance for CPPs is a list of experimental restrictions such as the number of possible experimental runs, easy/hard-to-change factors, randomization restrictions and design preferences.

Due to restrictions, cost, and time constraints, experiments in CPPs typically involve few factors, runs and replicates (Vanhatalo and Bergquist, 2007). Two-level (fractional) factorial designs are especially important to reduce the number of runs and factor level changes (Bergquist, 2015a). Box-Behnken designs also require few runs and are particularly suitable when extreme regions of the experimental space need to be avoided (Stazi et al., 2005; Kamath et al., 2011; Iyyaswami et al., 2013). Needs for restricted randomization, for instance to minimize long transition times, may necessitate split-plot designs (Sanders and Coleman, 1999; Bjerke et al., 2008; Vanhatalo and Vännman, 2008).

Response surface methodology (Box and Wilson, 1951; Myers et al., 2004) and evolutionary operation (Box, 1957) are two useful sequential experimental strategies when the goal is process optimization. Kvist and Thyregod (2005) demonstrate evolutionary operation for optimizing an industrial enzyme fermentation process.

Closed loop process operation

Applying EPC means running CPPs under closed-loop control, which complicates experimental design and analysis. Conventional DoE methods make the implicit assumption of open-loop operation in which effects of changes of experimental factors on responses may be studied directly. In closed-loop, many potentially interesting variables are kept around a certain values (set-points) to achieve desired product quality and/or for plant safety reasons. Potential effects of experimental factors on controlled variables are masked when manipulated variables are adjusted to counteract their deviations from set-points (Figure 2).

Capaci et al. (2017) suggest two closed-loop experimental strategies that classify the potential experimental factors as either a set of system inputs not involved in control loops or the actual control loop set-points, see Figure 2. In the former case, the manipulated variables become the responses. The experimenter can also use controlled variables as responses to study controller effectiveness. In the latter case, typical responses include overall process performance indicators such as cost and/or quality.

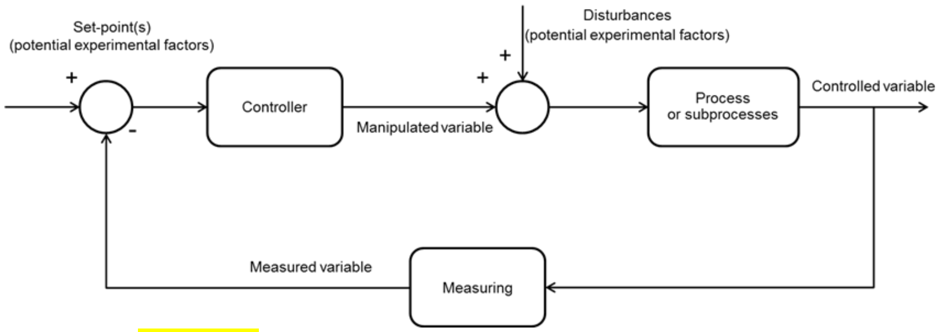

Figure 2. Schematic overview of process operating under closed-loop control

Process transitions and time series responses

High sampling frequencies in CPPs produce time series responses. Moreover, process dynamics often cause effects of experimental factors to develop gradually and then stabilize (Nembhard and Valverde-Ventura, 2003; Bisgaard and Khachatryan, 2011). These process transitions need consideration. Vanhatalo et al. (2013) develop possible analysis methods for experiments with time series responses. If the analyst can estimate the transition time (see for example Vanhatalo et al., 2010), the analyst can (i) use averages of the response in each run after eliminating transition time or (ii) use transfer function-noise modelling. However, transition times may prolong experimentation since it may be unclear when the process reaches steady state. Lundkvist and Vanhatalo (2014) apply a version of the second method to model time series of factors and responses of a full-scale blast furnace experiment. He et al. (2015) provide a recent review of additional available methods to analyse dynamic process responses in DoE.

Multivariate responses

Cross-correlations among responses often make multivariate analysis methods effective. Applications of multivariate projection methods such as PCA and PLS have been used to reduce the dimensionality and restrict the loss of information compared to univariate response analysis. A multivariate analysis approach also controls the Type I error rate. Vanhatalo and Vännman (2008) use principal components as new responses for a blast furnace experiment. El-Hagrasy et al. (2006), Baldinger (2012) and Souihi et al., (2013) provide additional multivariate analysis examples in DoE.

Conclusions and discussions

In this article, we focus our attention on discussing challenges of employing SPC and DoE for improving CPPs. Existing challenges do not mean that these methods cannot be used or should be discouraged. Similar or other challenges will be encountered also in other data analytics methods as in machine learning or neural networks. Managers of CPPs need to be aware that most employed methods have challenges that require special consideration in data-rich environments. This is true also in applying SPC and DoE. We are aware that many of the mentioned challenges are not unique for CPPs and lie outside of the general managerial knowledge domain. A managerial implication is thus to guide analysts to a proper choice of tools by posing questions of how to address the above mentioned challenges. We recommend that managers should solicit the competence of a statistically trained data analyst until process engineers have such competence themselves. This is especially true during SPC method selection, or when designing and analysing experiments.

Our literature review has revealed challenges in using SPC and DoE in CPPs, but also many remedies to overcome those challenges. Applications of SPC in CPPs are often multivariate, need to deal with autocorrelation and process transitions, as well as to work alongside EPC procedures. DoE may need to deal with the large-scale, closed-loop operation and multivariate time series responses. An important message is also that SPC and DoE methods can be applied readily using proper adjustments presented in the literature. We also recommend managers to make sufficient time and funding available to engineers and analysts to adapt methods and to acquire software that can support application. Softwares are continuously developing to meet some of the challenges we highlight in this article. Examples of commercial software that can aid the application of SPC in CPPs are Prosensus® (www.prosensus.com), Simca® (www.umetrics.com), and Unscrambler X® (www.camo.com). Available DoE software include JMP® (www.jmp.com), Design Expert® (www.statease.com), and Modde® (www.umetrics.com). For the more experienced analyst free software such as the R statistics software are interesting alternatives.

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