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Quality control and improvement for multistage systems: A survey

JIANJUN SHI[1,*] and SHIYU ZHOU[2]

[1] *School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, GA, 30332, USA*
E-mail: jianjun.shi@isye.gatech.edu
[2] *Department of Industrial and Systems Engineering, University of Wisconsin–Madison, Madison, WI 53706, USA*

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A multistage system refers to a system consisting of multiple components, stations or stages required to finish the final product or service. Multistage systems are very common in practice and include a variety of modern manufacturing and service systems. In most cases, the quality of the final product or service produced by a multistage system is determined by complex interactions among multiple stages—the quality characteristics at one stage are not only influenced by local variations at that stage, but also by variations propagated from upstream stages. Multistage systems present significant challenges, yet also opportunities for quality engineering research. The purpose of this paper is to provide a brief survey of emerging methodologies for tackling various issues in quality control and improvement for multistage systems including modeling, analysis, monitoring, diagnosis, control, inspection and design optimization.

Keywords: Multistage systems, quality engineering, variation modeling and reduction

1. The Characteristics of Multistage Systems

A multistage system refers to a system consisting of multiple components, stations or stages required to finish the final product or service. Multistage systems are very common in practice: (i) almost all modern manufacturing processes (e.g., assembly, machining, semiconductor fabrication, pharmaceutical manufacturing) fit this category; (ii) information systems consisting of multiple interconnected hosts to provide quick response to service requests also fit in this category; and (iii) service processes involving multiple processing steps to fulfill a customer's needs also fit in this category. For example, a plastic surgery operation, or a microvascular anastomosis procedure, involves about 15 surgical tasks (or stages), including positioning donor tissue, attaching the donor vein to the host, etc. Each task is completed by applying a set of surgical techniques. The performance quality of each task is measured by task outcome variables, which collectively impact patient outcomes.

Certain common characteristics make such systems inherently complex, including the following.

1. Multiple stages and hybrid structures with mixed sequential or/and parallel configurations.
2. Feedback/feedforward loops that arise because outputs from one stage are the inputs to other stages, so the outcomes from one stage are not only influenced by local variations at that stage, but also by the variations propagated from upstream stages, with the final outcome being an accumulation (or stack up) of variations from all stages.
3. Mixed data types and multiscale variables that arise from multiple processes or/and performance variables at each stage, which usually have different data types and different scales.
4. Collective and stochastic performance, i.e., the ultimate performance of the overall system depends upon the accumulated performance of individual stages in the system.

An illustrative diagram of a multistage system is shown in Fig. 1.

Figure 2 shows a manufacturing process for a dielectric electroluminescent Flat Panel Display (FPD). This process consists of various microfabrication operations, such as photolithography, sputtering, screen printing and laser machining (Madou, 2002). At each major station, there are five or six substations (not shown in the figure) at which tasks such as firing, curing, cleaning and inspection are performed. As a result, more than 40 high-precision steps are linked together to finish the final product. The layer-on-layer structure of the process means that the interactions

*Corresponding author

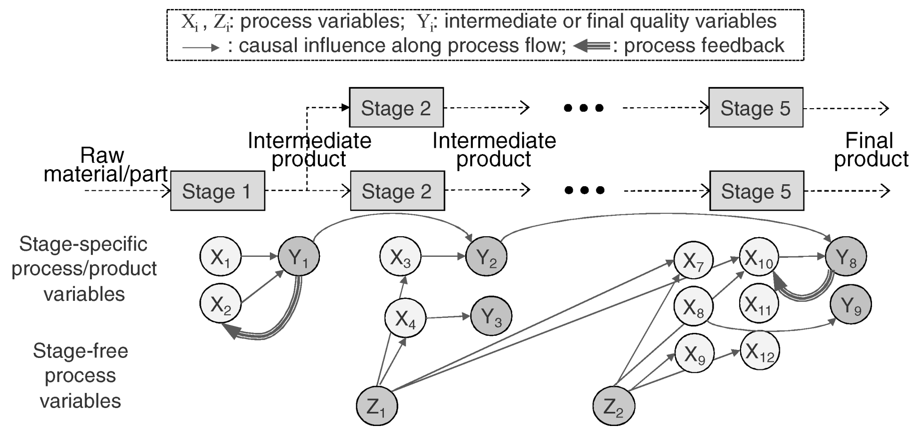

Fig. 1. A diagram of a multistage system.

among different stations are even stronger than those found in macro processes (Shindo *et al.*, 1998). For example, the evenness of each layer directly affects the uniformity of brightness of the display and thus is a critical quality characteristic; unevenness of one layer clearly affects subsequent layers. Thus, for yield improvement, the interactions among different stages must be considered.

Another typical example of a multistage system is the supply chain system, where the product is moved through multiple tiers of suppliers and eventually to the end customers. A well-known phenomenon, called the "bullwhip effect" in forecast-driven supply chains, is simply the result of the impact of stage-wise interactions on the system performance (Forrester, 1961). The concept of multistage systems is also relevant to chemical processes (Undey and Cinar, 2002), many service systems (Bolton and Drew, 1991), medical diagnosis (Chinchilli, 1983) and management systems (Beswick and Cravens, 1977). Many technical issues in system design, optimization and performance monitoring and evaluation can be investigated under the framework of multistage systems. For instance, extensive research exists on optimal scheduling and control of multistage production systems and supply chains, e.g., Liu *et al*. (2004), Sawik (1987), Gunasekaran *et al.* (1998) and Fenner *et al.* (2005). In order to limit the scope of this paper, we focus on the review of the quality control and improvement methodologies for multistage systems, particularly, multistage manufacturing systems.

The complexity of multistage systems presents significant challenges for effective quality control and improvement. Recent technological advances, on the other hand, provide us with great opportunities to develop new methodologies to understand and rise above these complexities. Due to the rapid development of information and sensing technologies, an abundance of data is now readily available in many real-world systems. In discrete manufacturing processes, total inspection at each intermediate operation and very high sampling rates are no longer rare in practice. For example, in automobile body assembly processes, 100% dimensional inspection has been achieved through in-line optical coordinate measurement machines (Ceglarek and Shi, 1995). In-line optical scanning systems are also widely available

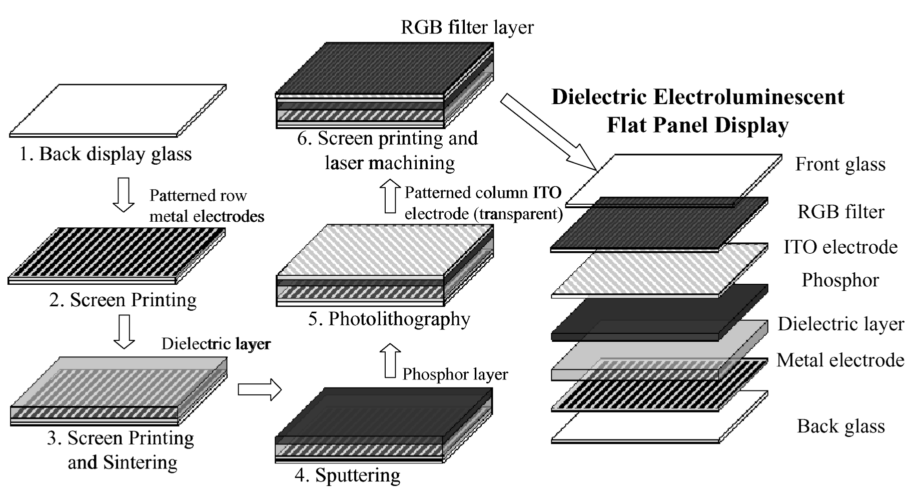

Fig. 2. A microfabrication process for a FPB.

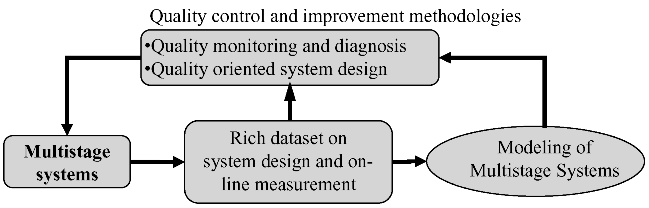

Fig. 3. The framework of multistage systems research.

in microfabrication processes (Raman *et al.*, 1998). This profusion of process/product measurement data provides opportunities for effective quality control. Through the full exploitation of the data-rich environment, many new quality control and improvement methodologies have been developed for multistage systems in recent years.

2. Quality control and improvement for multistage systems: State of the art

A basic framework for quality control research in multistage systems is illustrated in Fig. 3. Most of the recently developed quality control and improvement methodologies for multistage systems are built upon some sort of quantitative modeling of the system and can be classified into: (i) monitoring and diagnosis; and (ii) quality-oriented design optimization. In the following, we provide a brief review of each of these methodologies. A recent monograph (Shi, 2007) provides detailed descriptions of existing research on quality control for multistage manufacturing processes.

2.1. *Multistage system modeling for quality control*

The most challenging aspect of quality control for complicated multistage systems is process error accumulation and propagation along a series of stages. Thus, for quality improvement purposes, it is critical to establish a mathematical description of the interactions between process errors and the quality of final product in a multistage system. The current profusion of process/product information has presented great opportunities and indeed stimulated the development of modeling efforts for multistage systems.

Recent quantitative modeling methodologies for multistage systems can be roughly classified as analytical (employing physical models from engineering analyses) or data-driven (employing statistical models using only process measurement data) methods.

Analytical methods utilize off-line analysis of the system based on first principles, i.e., fundamental physical laws. The most popular physical model used for quality control of multistage systems is the state space model as shown in Fig. 4, first proposed in Jin and Shi (1999). In this method, the key quality characteristics of the product (e.g., the dimensional quality) at stage k are represented by state vector $\mathbf{x}_k$ and the process error sources (e.g., the fixture locator errors) at station k are included as inputs $\mathbf{u}_k$. The unmodeled errors are represented by a random vector $\mathbf{w}_k$. The vector $\mathbf{v}_k$ is the sensor noise. The state space model for a multistage system is expressed as:

$$\mathbf{x}_k = \mathbf{A}_{k-1}\mathbf{x}_{k-1} + \mathbf{B}_k\mathbf{u}_k + \mathbf{w}_k \quad \text{and } \mathbf{y}_k = \mathbf{C}_k\mathbf{x}_k + \mathbf{v}_k, \quad (1)$$

where $\mathbf{A}_{k-1}\mathbf{x}_{k-1}$ represents the transformation of product quality deviations from station $k-1$ to station k, $\mathbf{B}_k\mathbf{u}_k$ represents product deviations resulting from process errors at stage k and $\mathbf{C}_k$ maps product quality states to quality measurements. If the quality characteristics are directly measured, then $\mathbf{C}_k$ is simply an identity matrix. Matrices $\mathbf{A}_k$, $\mathbf{B}_k$ and $\mathbf{C}_k$ are determined through the first principle analysis of the system. This stage-indexed state space model had been used to model variation propagation in various multistation manufacturing processes, e.g., rigid-part assembly processes (Jin and Shi, 1999; Mantripragada and Whitney, 1999; Ding *et al.*, 2000; Huang, Lin, Bezdecny, Kong, and Ceglarek, 2007; Huang, Lin, Kong and Ceglarek, 2007; Liu, Jin and Shi, 2009), compliant-part assembly processes (Camelio *et al.*, 2003; Xie *et al.*, 2007), machining processes (Huang *et al.*, 2000; Zhou, Huang, and Shi, 2003; Djurdjanovic and Ni, 2001; Loose *et al.*, 2007, 2009) and sheet stretch forming processes (Suri and Otto, 1999).

The state space model is popular because it offers several advantageous features. First, the complicated stage-wise interaction is handled automatically in this model through the state transition. To construct this model, we only need to study locally the relationship among $\mathbf{x}_{k-1}$, $\mathbf{x}_k$ and $\mathbf{u}_k$ at each individual stage k. Hence, the large body of knowledge that may be available about each single-stage operation can be readily reused in the model construction. Furthermore, due to its chain-like structure, the state space model is very flexible. We can easily choose any critical segment of the process to model and analyze. The second advantage of this model is its linear structure. Although

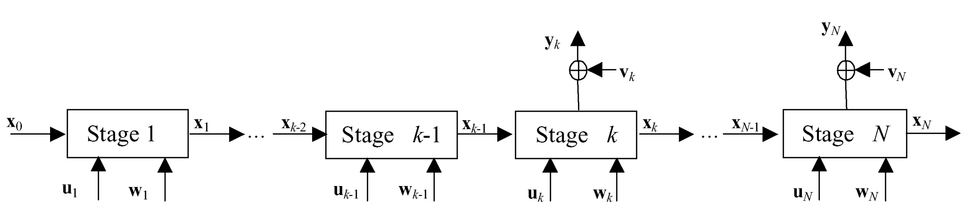

Fig. 4. Diagram of a multistage process.

the relationships among the key process and product factors are non-linear in general, those relationships can often be linearized around a nominal working status (Ren *et al.*, 2006). A linear state space model can significantly reduce the complexity of the subsequent analysis and synthesis. Indeed, after some straightforward manipulations, the state space models can be transformed to the following generic linear form:

$$\mathbf{y} = \boldsymbol{\Gamma}\mathbf{f} + \boldsymbol{\varepsilon}, \tag{2}$$

where $\mathbf{y}$ is a vector consisting of product quality characteristics, $\boldsymbol{\Gamma}$ is a constant coefficient matrix determined by the process/product design, $\mathbf{f}$ is a vector representing the process error sources and $\boldsymbol{\varepsilon}$ includes measurement noise and unmodeled system variation.

The physical models are derived from first principles that characterize the process. Such models can usually provide useful insights on how the sources of variation affect product quality. However, the physics of the process needs to be thoroughly studied to construct the process model. Different from physical models, data-driven models focus on investigating patterns in the massive historical quality database to estimate the coefficient matrix $\boldsymbol{\Gamma}$ and thus do not require comprehensive *a priori* knowledge of the process. Some authors have employed a data-driven AR(1) model to describe the variation transmission in both multistage assembly and machining processes (Agrawal *et al.*, 1999; Lawless *et al.*, 1999). The parameters of their AR(1) model are estimated based on product measurements. Factor analysis (Apley and Shi, 2001; Liu *et al.*, 2008) and blind source separation techniques (Apley and Lee, 2003; Shan and Apley, 2008) have been used to estimate $\boldsymbol{\Gamma}$. These methods rely on assumptions of a specific quantitative or qualitative structure of the coefficient matrix $\boldsymbol{\Gamma}$ or certain conditions on the autocorrelation or distribution of the variation sources and process noise. Another data-driven modeling technique is based on the analysis of the linear space spanned by the eigenvectors of the covariance matrix of the multivariate quality measurements (Krzanoski, 1979; Johnson and Wichern, 2002; Jin and Zhou, 2006a, 2006b). This technique builds upon the fact that given model (2), the eigenvectors of $\mathbf{y}$ possess some specific relationships with the matrix $\boldsymbol{\Gamma}$. The aforementioned methods can effectively identify the structure of the aggregated $\boldsymbol{\Gamma}$ matrix based on the measurements of quality characteristics. However, the stage-wise interactions cannot be identified. Recently, data-driven techniques were proposed to statistically infer the direct interactions among different stages (Zeng and Zhou, 2007; Li and Shi, 2007). These techniques identify the underlying interactions among stages through the integration of advanced statistical techniques (e.g., graphical models (Zeng and Zhou, 2007) and causal Bayesian network models (Li and Shi, 2007)) and engineering insights regarding manufacturing processes.

The aforementioned mathematical models provide quantitative foundations for quality analysis, diagnosis and control in complicated multistage processes. Building upon these models, various quality control and improvement methodologies have been developed, as we describe in the next section.

2.2. *Monitoring, diagnosis and control for multistage systems*

2.2.1. *Statistical process monitoring for multistage systems*

In quality control and improvement, it is critical to monitor the process to detect process changes and further diagnose the process to determine the root causes of the changes.

Statistical Process Control (SPC) is the main technique used in practice for quality and process monitoring. However, most conventional SPC techniques treat the multistage system as a whole and lack the capability to discriminate among changes at different stages (see Montgomery and Woodall (1997) for reviews). A major challenge in applying these techniques to a multistage system is the high false alarm rate, i.e., a change is detected at a stage, but the change is actually due to a change at preceding stages. Thus, a monitoring technique should take the stage-wise interactions into consideration to reduce the false alarm rate. Existing techniques include regression control charts (Mandel, 1969) and cause-selecting control charts (Zhang, 1985; Wade and Woodall, 1993), where the outgoing quality is monitored after adjustment for the effect of the incoming quality. Hawkins (1991, 1993) proposed an extension of this methodology and studied the design of related procedures for monitoring correlated quality characteristics based on regression adjustment in cascading processes. He suggested that every quality characteristic should be monitored by a corresponding regression-adjusted chart, which is based on the (standardized) residuals, $Z_j = Q_j - \hat{Q}_j$, $j = 1. \ldots .q$, called regression-adjusted variables. The residuals are the results when the observation of the quality characteristic at the jth stage, denoted as Q_j, is regressed against the measurements of the quality characteristics of all its preceding stages. In this way, the stage-wise interactions are adjusted and if Z_j is out of control, it means that some faults occurred on the jth stage. The idea of regression adjustment is widely accepted as a good way to deal with multistage quality control problems and has become the basis for some further studies. For example, Zantek *et al.* (2002) measured the impact of each stage's performance on variations in intermediate and final product quality. This idea has also been extended to multivariate cases (Hauck *et al.*, 1999). The impact of measurement errors on the performance of regression-adjusted monitoring also has been investigated (Zeng and Zhou, 2008). Besides regression-adjusted methods, some multivariate SPC techniques (e.g., Nomikos and MacGregor (1995) and Kourti and MacGregor (1996)) such as principal components analysis and partial least squares are able to handle large, ill-conditioned measurement spaces and thus have the potential to be applied to multistage system monitoring as well. Most recently, some specific SPC techniques have been developed to exploit the detailed structure of multistage systems to achieve high detection power and diagnostic capability. For example, an exponential weighted moving average scheme has been proposed as a monitoring method for multistage systems (Xiang and Tsung, 2008; Zou and Tsung, 2008). Methodologies for identifying in-control samples and adjusting the detection power for multistage systems have been reported as well (Zou *et al.*, 2008; Li and Tsung, 2009).

2.2.2. *Root cause identification for multistage systems*

After a process change is detected through SPC techniques, it is critical to determine the root causes and identify appropriate corrective actions to restore the system to its normal condition. However, SPC methods generally do not provide diagnostic capability—the diagnosis of root causes is left to human operators. Stimulated by the availability of measurement data and the development of modeling techniques for multistage systems, significant progress has been made toward intelligent root cause diagnostics. These methodologies can be roughly classified into two categories: (i) statistical-estimation-based methods; and (ii) pattern-matching-based methods. Both of these methods are based on mathematical models that link the system error and the system quality measurements as given in Equations (1) and (2).

In estimation-based methods, model (2) is treated as a linear mixed model. The variances of process errors $\mathbf{f}$ are the variance components to be estimated in this mixed model (Searle *et al.*, 1992; McCulloch and Searle, 2001). One method uses ordinary least squares to estimate the random input $\mathbf{f}$ and then calculates its variance as if the estimates were directly measured (Apley and Shi, 1998; Chang and Gossard, 1998). Zhou *et al.* (2004) used a maximum likelihood estimator and also provided confidence intervals for the estimated variance of $\mathbf{f}$. Ding, Zhou and Chen (2005) compared different variance estimation methods and provided guidelines for method selection under different circumstances.

The basic idea underlying the pattern-matching-based method is as follows. First, based on the model, we can obtain signatures of potential errors. Meanwhile, symptoms of the present error can be extracted from measurement data. Finally, the present error can be identified if there is a match between the patterns of the error symptom and the error signature. In most available pattern matching techniques (e.g., Ceglarek and Shi (1996), Rong *et al.* (2000), Ding, Jin, Ceglarek and Shi (2002a) and Li *et al.* (2007)), the columns of $\mathbf{\Gamma}$ are treated as the signatures of corresponding errors and it is assumed that during the data collection period, only one error occurs in the system. In these approaches, the eigenvector associated with the largest eigenvalue of $\mathbf{S}_\mathbf{y}$ (the sample covariance matrix of $\mathbf{y}$) is calculated and compared with the columns of $\mathbf{\Gamma}$. If there is a match, then we can conclude that the corresponding error occurred in the system. These methods are extended to cases with multiple errors in Jin and Zhou (2006a), Li and Zhou (2006) and Kong *et al.* (2008), and are also implicitly embedded in the rule-based fault isolation approach (Ceglarek *et al.*, 1994). Some subtle aspects of the pattern matching method such as construction and integration of signatures in the case of multiple errors have been investigated as well (Jin and Zhou, 2006b; Zeng *et al.*, 2008). Most existing pattern matching methods only consider the linear patterns. However, a pattern matching method based on non-linear relational measurements was also reported recently (Loose *et al.*, 2008).

A question that is common to both methods mentioned above concerns system diagnosability: does the system measurement data contain sufficient information to enable us to differentiate system errors at different stages? The concept of diagnosability of multistage system was initially proposed in Ding, Shi and Ceglarek (2002). The issue of diagnosability has been systematically investigated under the framework of linear mixed models. Quantitative criteria for checking diagnosability and the useful concept of a minimal diagnosable class have been proposed (Zhou, Ding, Chen and Shi, 2003). Researchers have found that system diagnosability is closely related to the structure of the $\mathbf{\Gamma}$ matrix in Equation (2) and the structure of a quadratic transformation of $\mathbf{\Gamma}$. Other easy-to-use diagnosability checking criteria were also recently developed (Ding *et al.*, 2004; Zhang *et al.*, 2007; Chen and Zhou, 2009). Apley and Ding further developed unified formulations and solution procedures to transform various forms of singular, non-diagnosable assembly systems into full-rank, diagnosable systems (Apley and Ding, 2005).

The statistical-estimation-based method and the pattern-matching-based method have different strengths. From a practical point of view, the pattern matching method is very intuitive and possesses a clear geometric interpretation, which may help practitioners understand and eliminate the variation source. Thus, the pattern matching method is more readily accepted by practitioners than are statistical estimation methods. On the other hand, using statistical estimation methods, people can evaluate the performance of statistical tests quantitatively because the statistics used in the tests are tractable.

As an extension of diagnosis methodologies, some researchers developed a process adjustment technique to reduce the variation in a multistage system. The basic idea is to control the product quality through on-line adjustment of certain process parameters such as the fixture locations. The control algorithms are based on an understanding of the process operation derived from the multistage system model and are often in feedforward form. These techniques have been developed for both assembly (Izquierdo *et al.*, 2007) and machining processes (Djurdjanovic and Ni, 2007).

2.3. *Quality-oriented design optimization*

Multistage systems provide significant opportunities for the establishment of new methodologies for design optimization with the goal of quality improvement and reduction of inspection cost. System design is a very broad field and the design problems can be classified into two basic categories: (i) quality inspection strategy design; and (ii) process parameter design. The goal of designing a quality inspection strategy is to optimize the allocation of inspection resources and determine the optimal parameters for the quality assurance program, while the role of process parameter design is to adjust the process design itself to improve the robustness and accuracy of the process itself in order to produce a better quality product. These two design problems are essentially engineering optimization problems that differ from one another in their objective functions. Multistage systems pose significant challenges and, at the same time, opportunities for solving both these design problems.

In a recent survey (Mandroli *et al.*, 2006), inspection strategy design is further classified into two categories: inspection-oriented quality assurance strategies and diagnosis-oriented sensor distribution strategies. The first focuses on minimizing the total system cost for quality appraisal by adjusting the inspection parameters (e.g., fraction of items to be inspected, number of repetitions in inspection, protocols for dealing with non-conforming items, etc.) and optimally allocating inspection capabilities to various stages in the system. These strategies are called "quality assurance" strategies because they ensure that the customer will receive high-quality product. However, these strategies usually do not provide feedback for improvement of the process itself. On the other hand, the second category, sensor distribution strategies, focuses on optimal sensor distribution in the system with the goals of minimizing cost and maximizing the diagnosability of the system. Clearly, these strategies focus on quality control and continuous improvement of the process itself. Extensive research exists in both of the aforementioned areas. However, since an excellent survey on these strategies appears in Mandroli *et al.* (2006), we do not review these streams of research here.

The use of a quantitative framework for modeling variation in multistage systems enables us to optimize process parameters for quality control and improvement. For example, given the key process characteristics ($\mathbf{u}_k$), we can obtain the mean and the variance of the measurable key product quality characteristics ($\mathbf{y}_k$) based on an analysis of the multistage model (1). The results of this analysis can be immediately used to study the sensitivity of $\mathbf{y}_k$ to $\mathbf{u}_k$. We can identify process factors that have large impacts on product quality so that we can focus on those factors when trying to improve quality. Indeed, such a sensitivity study for multistage manufacturing processes has been reported (Ding, Ceglarek and Shi, 2002b). Based on this sensitivity study, two approaches for quality improvement via adjustment of the design can be pursued: (i) optimal allocation of tolerances for the $\mathbf{u}_k$ values; and (ii) changing the structure or parameters of the process (i.e., change the matrix $\boldsymbol{\Gamma}$ in model (2)) to reduce the sensitivity or "gain" of the system. Mathematically, both problems can be formulated as constrained optimization problems given by

$$C_{\mathbf{T}}(\mathbf{T}^*) = \min_{\mathbf{T}} C_{\mathbf{T}}(\mathbf{T}) \quad \text{subject to } \Im(\mathbf{T}) < \boldsymbol{\Xi} \tag{3}$$

where $\mathbf{T}$ is the vector of process parameters we are trying to adjust, $\Im(\mathbf{T})$ represents the production cost associated with the selected set of process parameters $\mathbf{T}$, $C_{\mathbf{T}}$ is a given measure or index of the sensitivity of product quality deviation with respect to process parameters $\mathbf{T}$ and $\boldsymbol{\Xi}$ is a specified cost level. By solving this problem, we can minimize product quality variation under a cost constraint. Under certain conditions, a quadratic cost function and a simple linear function $C_{\mathbf{T}}(\mathbf{T})$ can be used in this design optimization problem. This will lead to a closed-form solution to this problem. Then, physical insights and guidelines for process improvement can be realized. For a multistage system, the critical challenge in solving the above optimization problem is the high dimensionality of $\mathbf{T}$, i.e., for a complicated multistage system, there are usually a large number of process parameters to adjust. A dimension reduction technique is often needed before solving model (3). In the literature, both approaches to design improvement have been investigated. The optimal tolerance allocation problem is studied in Huang and Ceglarek (2004), Ding, Jin, Ceglarek and Shi (2005), Chen *et al.* (2006), Phoomboplab and Ceglarek (2007) and Huang *et al.* (2009), while the process structure/parameter optimization is investigated in Kim and Ding (2004, 2005), Phoomboplab and Ceglarek (2008) and Liu, Shi and Hu (2009). As a specific example of the latter, an interesting data-mining-guided method has been proposed to handle the high dimensionality issue (Kim and Ding, 2005). Efforts also have been made to integrate tooling reliability and product quality in multistage systems in the so-called "Quality and Reliability Chain" model (Chen and Jin, 2005) for system design and evaluation (Chen *et al.*, 2004).

From the above review, we can see that vast amounts of information from product design, process design, in-process sensing and product quality inspection can be integrated under a unified quantitative framework for multistage systems. This integrated framework lays a foundation for developing advanced process monitoring, diagnosis and control methodologies by using systems theory and advanced statistics and indeed has spurred an impressive amount of research work in recent years.

3. Future trends

The complexity of multistage systems requires a holistic system-level approach for effective quality control. Thus, the essence of the multistage system framework is the fusion of theories, tools and techniques from multiple disciplines such as industrial and systems engineering, statistics, mechanical engineering and electrical engineering to achieve full utilization of the wide spectrum of readily available information. Indeed, this has been an ever-growing trend in many academic disciplines. Computational power and the data availability have reached unprecedented levels in recent years, thanks to the information revolution. New methods to exploit these opportunities to establish transformative methodologies for solving engineering problems will be at the center stage of engineering research in the future. Research on multistage systems will follow the same trend. Specifically, we believe the following research areas in multistage systems will grow significantly.

First, analysis of complex systems using modeling based on first principles is often intractable. Consequently, data-driven modeling and knowledge discovery for multistage systems will become more popular. The data may come from system sensors or the output of a high-fidelity numerical simulation model. Data mining and surrogate modeling for multistage systems will become very active research areas.

Second, system design is always a critical issue in product and service realization. For many years, researchers and practitioners have advocated the integration of product design with manufacturing systems design. A new term, "Design for X" was even coined for this effort. The research on quality control and improvement for multistage systems will lead to a quantitative foundation for integrated product and process design. Some existing work on multistage systems, e.g., the work on process-oriented tolerancing, has demonstrated this capability. We expect that more research will be conducted along this line. The key challenges in integrated design such as design space characterization and solution of high-dimensional design optimization problems will be conquered in the near future.

Third, as mentioned in the previous sections, quantitative models of quality in multistage systems can be applied to a very broad range of systems, although existing research mostly focuses on discrete parts manufacturing processes. The success of the framework for multistage systems in quality control of multistage manufacturing systems will certainly stimulate the extension of this methodology to other systems and fields. For example, the monitoring and diagnosis of abnormalities in the throughput, cycle time and lead time of a multistage production system will be very promising application areas for the multistage systems framework. Most service systems such as healthcare clinics and hospitals and transportation systems are inherently multistage. Quality control and improvement for such systems will definitely benefit from the framework for multistage systems.

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Biographies

Jianjun Shi is a Professor and holds the Carolyn J. Stewart Chair Professorship at the H. Milton Stewart School of Industrial and Systems Engineering, Georgia Institute of Technology. Before joined Georgia Tech in 2008, he was the G. Lawton and Louise G. Johnson Professor of Engineering at the University of Michigan. He received his B.S. and M.S. in Electrical Engineering at the Beijing Institute of Technology in 1984 and 1987 respectively, and his Ph.D. in Mechanical Engineering at the University of Michigan in 1992. His research interests focus on the fusion of advanced statistics, signal processing, control theory and domain knowledge to develop methodologies for modeling, monitoring, diagnosis and control for complex systems in a data-rich environment. He is the founding chairperson of the Quality, Statistics and Reliability (QSR) Subdivision at INFORMS. He currently serves as the Focus Issue Editor of *IIE Transactions on Quality and Reliability Engineering*. He is a Fellow of the Institute of Industrial Engineering (IIE), a Fellow of the American Society of Mechanical Engineering (ASME), and a Fellow of the Institute of Operations Research and Management Science (INFORMS). He is also a member ASQ, SME, and ASA.

Shiyu Zhou is an Associate Professor in the Department of Industrial and Systems Engineering at the University of Wisconsin-Madison. He received his B.S. and M.S. in Mechanical Engineering at the University of Science and Technology of China in 1993 and 1996 respectively, and his Master's in Industrial Engineering and Ph.D. in Mechanical Engineering at the University of Michigan in 2000. His research focuses on developing in-process quality and productivity improvement methodologies by integrating statistics, system and control theory, and engineering knowledge. The objective is to achieve automatic process monitoring, diagnosis, compensation and their implementation in various manufacturing processes. His research is sponsored by National Science Foundation, Department of Energy, NIST-ATP and industries. He was a recipient of the CAREER Award from the National Science Foundation in 2006. He is a member of IIE, INFORMS, ASME and SME.