

Recent Developments and Industrial Applications of Data-Based Process Monitoring and Process Control

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Abstract

Statistical process monitoring and control are now widely accepted in various industries. In recent years, statistical techniques are expected to solve quality-related problems. The issue of how to improve product quality and yield in a brief period of time becomes more critical in many industries where the product life cycle becomes shorter. Examples include steel processes and semiconductor processes. These processes are totally different in appearance, but the problems to solve are highly similar: how to build a reliable model from a limited data, how to analyze the model and optimize operating condition, and how to realize an on-line monitoring and control system and maintain it. In this paper, the problems and solutions are described with our application results in steel facilities.

Keywords: Statistical Quality Control, Statistical Process Control, Multivariate Analysis, Iron and Steel Process.

1. Introduction

How can we improve product quality and yield? More than ever, the answer to this question is vital as product life cycles are getting shorter and international competition is getting keener. Since this question arises repeatedly when a new product is developed, quality improvement should be achieved faster and in a more systematic way. Statistical quality control (SQC) has been widely used to address this issue and to search for an operating condition that can achieve the desired quality through designed experiments. However, designed experiments are impractical in more than a few industrial processes, because they require considerable time and cost. Jaeckle and MacGregor (1998) proposed a data-based method for determining the operating condition that can achieve the desired product quality. Kano et al. (2004) extended the method to cope with qualitative quality as well as quantitative quality and applied it to steel making and finishing processes. The proposed method is referred to as Data-Driven Quality Improvement (DDQI). On the other hand, in various industries, run-to-run (R2R) control has been widely used to control the product quality by manipulating operating conditions between batches (Castillo and Huriwitz, 1997), and multivariate statistical process control (MSPC) has been widely used to detect and diagnose faults (Kourti and MacGregor, 1995).

In this paper, a newly developed process control and monitoring system for product quality and yield improvement, referred to as hierarchical quality improvement system (HiQIS), is presented. HiQIS consists of DDQI, R2R control, local control, and MSPC. Among these elements, DDQI, which is based on a statistical model, plays the most important role. It can cope with qualitative as well as quantitative variables, build

a partially nonlinear model, determine the operating conditions that can achieve the desired product quality, optimize operating condition under various constraints, select manipulated variables suitable for R2R control, and thus can provide useful information to improve product quality. This paper aims to give an outline of DDQI and HiQIS and to show their usefulness via industrial case studies.

2. Hierarchical Quality Improvement System (HiQIS)

In the process industry, a hierarchical control system has been widely accepted. The most famous one would be a model predictive control system which is integrated with a steady-state optimizer and local controllers. Qin et al. (2004) proposed a hierarchical fab-wide control framework in the semiconductor industry. The fab-wide control system is analogous to the model predictive control system. The hierarchical quality improvement system (HiQIS) is also an analogue to them. A schematic diagram of HiQIS is shown in Fig. 1. DDQI is a process analysis system located at the top of the hierarchy. It constructs a statistical model from operation data, analyzes the cause of inferior quality and low yield, selects manipulated variables, and optimizes the operating conditions that can achieve the desired quality. R2R control updates operating conditions or operation profiles for the next batch and gives set-points to local controllers on the basis of information provided by DDQI. In addition, MSPC detects and diagnoses faults on the basis of the statistical model built in DDQI. In this section, R2R control and MSPC are briefly reviewed.

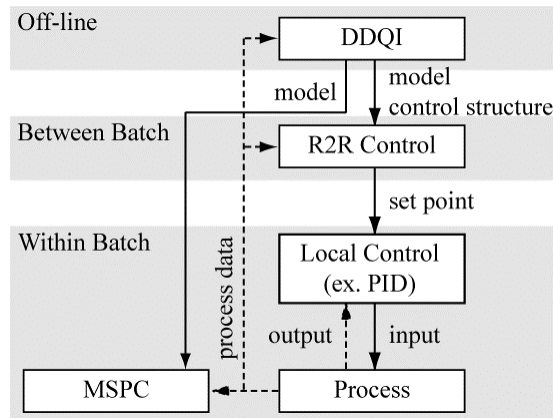


Figure 1. A schematic diagram of hierarchical quality improvement system (HiQIS).

2.1. Run-to-Run Control

Run-to-Run (R2R) control is a form of discrete control in which the product recipe is modified *ex situ*, i.e., between runs, so as to minimize process drift, shift, and variability. There are several R2R control algorithms. One widely used R2R controller is based on the exponentially weighted moving average (EWMA) statistic to estimate process disturbances. Although EWMA has been used for a long time for quality monitoring, its use for R2R control is relatively recent. Since the early 1990's, R2R control techniques have been developed and used to control various semiconductor manufacturing processes (Castillo and Huriwitz, 1997).

2.2. Multivariate Statistical Process Control

For the successful operation of any process, it is important to detect process upsets, equipment malfunctions, or other special events as early as possible and then to find and remove the factors causing those events. In industrial processes, data-based process monitoring methods, referred to as statistical process control (SPC), have been widely used. To improve the monitoring performance, multivariate statistical process control (MSPC) has been developed. The original Shewhart-type control chart for correlated variables is the Hotelling T^2 control chart. Later, PCA was used as a tool of MSPC, and the control charts were introduced for the sum of squared errors (SPE) as well as T^2 of principal components retained in a PCA model. In the last decade or so, various extensions of MSPC have been proposed (Kourti and MacGregor, 1995). When an out-of-control signal is detected, it is necessary to identify the process variables that cause the out-of-control signal. This information helps operators to further diagnose the actual cause of a fault. For this purpose, contribution plots are widely used.

3. Data-Driven Quality Improvement (DDQI)

In this section, Data-Driven Quality Improvement (DDQI) is focused. Jaeckle and MacGregor (1998) proposed a product design method based on linear/nonlinear multivariate analysis. Although their method can derive the operating conditions that can achieve the desired product quality, it does not account for qualitative variables. DDQI can handle qualitative as well as quantitative variables in a unified framework. In addition, DDQI has several additional important functions.

3.1. Modeling Quality and Operating Conditions

DDQI is based on a statistical model that relates operating conditions with quality. To cope with a collinearity problem, principal component regression (PCR) or partial least squares (PLS) are usually used. The derived coefficient matrix shows the influence of operating conditions on product quality. Although PCR and PLS are useful for building a quality model, they cannot cope with process nonlinearity. On the other hand, nonlinear modeling methods such as artificial neural networks are not always desirable because limited samples make it difficult to build a reliable nonlinear model and also its interpretation is difficult. Therefore, in DDQI, analysis of variance (ANOVA) is integrated with statistical modeling method. First, a linear regression model is built by using PCR or PLS. Then, ANOVA is applied to operation data after operation data of each input variable are classified into two or more levels. ANOVA clarifies whether significant interaction exists between specific variables. If it exists, then an interaction term is introduced into the quality model. In addition, nonlinearity between prediction error and each input variable is analyzed, and a quadratic term is introduced if necessary. This approach can generate a simple quality model with minimum nonlinear terms. As a result, the derived model is easy to analyze and interpret.

3.2. Optimizing Operating Condition

To determine the operating conditions that can achieve desired product quality, an inverse problem of the statistical model is solved. In general, the number of quality variables is less than that of principal components, and thus, the operating condition cannot be determined uniquely. However, it can be optimized when an objective function is provided. The objective function is optimized under the following four constraints: 1) the desired product quality is achieved, 2) the operating condition exists in the space spanned by principal components, 3) all operating condition variables exist within their upper and lower bounds, and 4) T^2 statistic of scores is below its upper control limit or approximately 4) all scores exist within their upper and lower bounds.

The last constraint is necessary for finding a new optimal operating condition within the region where the statistical model is valid. In other words, extrapolation should be avoided by using the last constraint. If there is no solution that satisfies all constraints, i.e., the imposed specifications on quality are too severe, the operating condition that achieves as desired quality as possible should be determined.

3.3. Handling Qualitative Variables

In the previous subsection, the method to optimize the operating condition that can achieve the desired product quality is explained. However, it is applicable only to cases where all quality variables are quantitative. When the quality variables are qualitative, e.g., good and bad, the desired product quality cannot be specified quantitatively. To cope with this problem, a novel quantification method was proposed (Kano et al., 2004).

To build a quality model by using PCR, qualitative variables should be quantified. As is well-known, for example, qualitative information such as good and bad can be quantified and denoted by 1 and 0, respectively. This conventional quantification method is useful for building a quality model, but not for solving its inverse problem. A serious problem is that the physical meaning of the quantified variable is not clear at all. For example, what does 0.6 mean? Is it acceptable or not? Nobody can answer this question. For a qualitative quality variable, the yield, i.e., the percentage of good products to all products, can be specified instead of the quality itself on the basis of the histogram for each category. Each histogram can be obtained from operation data, and it can be drawn as the frequency distribution of good or bad samples against the discriminant axis defined by PCA-LDA, which is the integration between principal component analysis (PCA) and linear discriminant analysis (LDA). Then, the yield against the discriminant axis can be derived. Once the desired yield is specified, operating conditions that can achieve the desired yield can be found by following the above-mentioned approach.

4. Applications to Industrial Iron and Steel Process

In the iron and steel industry, process control systems have been designed by using mathematical models that describe the relationship between controlled product quality variables and manipulated variables. However, the relationship of operating condition to product quality such as surface flaws and internal defects is not clear. In general, these qualities have been maintained by skilled operators on the basis of their experience and intuition. It is empirically known that the occurrence of surface flaws and internal defects is affected by operating conditions of a furnace in a rolling process and a continuous casting equipment in a steel making process. However, it is not clear which operating condition has an influence on qualities to what extent. In addition, since internal defects are checked by using ultrasonic testing after a rolling process, it may take a few days to get control results in a steel making process, and thus real-time control cannot be applied to this type of quality control problem. To improve product yield, it is important to predict final product qualities. Due to these characteristics, surface flaws and internal defects have not been the target of process control for many years. However, business situation is changing. To meet customers' requirements for higher product quality, to realize higher product yield, and to cope with decrease in skilled operators (Year 2007 problem in Japan), most iron and steel companies have started to cope with qualities such as surface flaws and internal defects within a framework of process control. Recently, the authors have investigated a statistical approach to address this problem and succeeded in improving product yield in iron and steel processes shown in Fig. 2 (Kano et al, 2005).

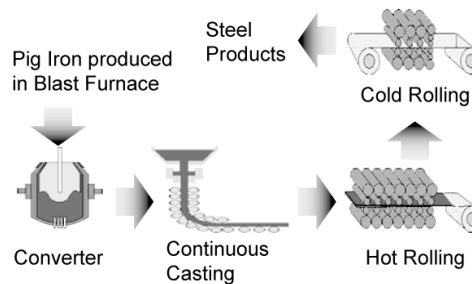


Figure 2. Schematic diagram of iron and steel process to investigate.

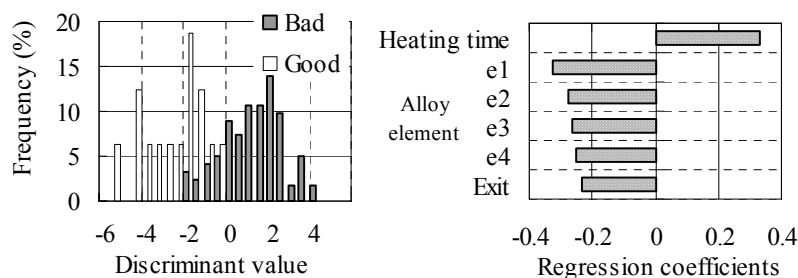


Figure 3. Results of PCA-LDA. (left) Discrimination between good products and bad products. (right) Top six regression coefficients.

4.1. Reduction of Surface Flaws

Reducing surface flaws is crucial for improving product yield. Surface flaws are checked after cold rolling as one of the key product qualities, and their shape and size are varied depending on their factors and steel grades produced. In this application, surface flaws frequently occurring in a specific alloy steel product are investigated. It is empirically known that the occurrence of surface flaws is affected by operating conditions of a rolling process and a steel making process. A large amount of defective steel is produced if steel making causes surface flaws, because surface flaws cannot be detected before the final inspection process. Therefore, it is important to clarify the cause of surface flaws, to find the operating condition that can minimize them, and to realize setup control. Here, application of PCA-LDA to this problem is described. First of all, a model relating operating conditions in steel making and hot rolling as input variables to surface flaws inspection results as an output variable was developed. Input variables include contents of various additive elements in a steel making process, temperature and residence time in each heating zone in a hot rolling process, and temperature at the exit of each stand in a hot rolling process. A total number of input variables selected is 55. The sample number is 138 consisting of 122 samples with surface flaws, classified into bad, and only 16 samples without surface flaws, classified into good. The dimensionality was reduced from 55 to 6 via PCA after all variables were normalized. Then, LDA was used for discriminating between two classes, i.e., good and bad. The developed PCA-LDA model was able to successfully discriminate between good products and bad products along the discriminant axis as shown in Fig. 3. This PCA-LDA model can relate operating conditions with the product yield through the proposed quantification method. Six variables having the largest influence on the product yield are listed in Fig. 3 with their regression coefficients. On the basis of this

result, process engineers selected to manipulate alloy element e1 considering both operation cost and operability. Figure 3 suggests that surface flaws can be reduced by increasing the content of alloy element e1. It is confirmed from the verification experiments that surface flaws can be significantly reduced by increasing the content of alloy element e1.

4.2. Reduction of Internal Defects

The objective in this application is to minimize internal defects. The target process consists of a steel making process, a blooming process, and a bar rolling process. Internal defects are checked by using ultrasonic testing (UST) after the bar rolling process. In this application, 40 operating condition variables are selected as input variables. The sample number is 740 consisting of 208 samples with internal defects and 532 samples without internal defects. The number of principal components retained is five. The developed PCA-LDA model was able to discriminate between good products and bad products along the discriminant axis. On the basis of the PCA-LDA model, process engineers selected to manipulate two factors in the steel making process and one factor in the blooming process considering both operation cost and operability. The next step is to optimize operating conditions via DDQI. The optimal operating condition that can improve the product yield by 20% is searched. To verify the results, test experiments were performed at the operating condition close to the optimal point, and it was confirmed that the percentage of defective product was reduced by half.

5. Conclusions

To date, HiQIS and DDQI have been tested in the steel, the semiconductor, and the liquid crystal display industries, and have succeeded in finding new operating conditions to achieve higher product quality. As the product life cycle becomes shorter, the issue of how to improve product quality and yield in a brief period of time becomes more critical in many industries. How can we improve product quality and yield? From the authors' experience of applying HiQIS and DDQI to several industrial processes, the author hopes to develop a unified framework that can answer to this question on the basis of data-based methodologies. Of course, process knowledge is the key to success. Although different knowledge and models are required for coping with different processes, a data-based quality improvement framework could be applied to any process in various industries.

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