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Use of Continuously monitored Data in Product Improvement

Project: A92-2

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Introduction

One of the latest trends in automation is the use of continuous monitoring systems to record defects and measure quality on-line. The continuous monitoring of a process often produces more data than manufacturers are equipped to use profitably. Continuous correction of a process based on a data stream often may actually decrease product quality or mask problems which need attention. Since the continuous monitoring technology is available and since, in many cases, a textile manufacturer has already paid for the information, he should use it to full advantage.

Statistical Quality Control (SQC) was designed to sample a large population on an infrequent basis. Thus, only a small portion of the product was evaluated for quality. Many people believe that with complete testing of the product (or continuous monitoring of the process), there would be no need for SQC. Such an attitude assumes that the function of SQC is to catch the defective product before it reaches the customer (i.e. acceptance sampling), but ignores the potential for statistics as a tool in product improvement. In recent years, the SQC techniques which worked well for final product quality control have been applied to materials in process and to process conditions. The procedure is now known as SPC or Statistical Process Control. Some of the SPC techniques which work for infrequent sampling may not work for very frequent or continuous sampling. How to use data which evolves from continuous sampling particularly with feedback control, is particularly troublesome.

Developments in sliver, yarn, and fabric monitoring systems pose the logical question of how to use the data generated by these systems in a more effective SPC program. Continuous measurements and collection of data have added a new dimension to SPC by providing 100% inspection of intermediate and final products. Unfortunately, this capability has not been fully utilized in the textile industry. A recent survey by the principal investigators found that only 5% of the information provided by the monitoring systems is utilized in the textile industry. For example, in monitoring systems used on spinning, warping, slashing, and weaving machinery, the primary figure obtained was the efficiency. Other information such as end-breakage, yarn defects, fabric defects, etc. were not used. In addition, integrating the monitored data into a SPC system was found to be either inefficient or non existent. Several manufacturers have pointed out reasons why they do not use more of the generated data:

a. The absence of continuous fiber information [i.e. continuous monitoring of fiber properties from one stage to another]. This makes utilization of information provided by existing monitoring systems of sliver, yarn, and fabric largely limited.

b. The sheer volume of data generated - (1 to several hundred data points per second)

c. The lack of experts in the use of continuously monitored data in a feedback or a feedforward information system.

d. Some of the monitoring systems available are generic, and are made by electronic specialists with limited pre-consultation with textile technologists or engineers.

e. The variable nature of raw material and, consequently, the complex nature of machine/material interaction. This makes it difficult to rationalize continuous output data.

f. The lack of established procedures to use continuous data in an integrated quality system.

Current technology allows the on-line measurement (and often the control) of evenness in card feed, card sliver output, drawn sliver, and yarn. While existing monitoring systems do not detect fiber characteristics throughout the textile process, such monitoring capability is coming. Even today, off-line testing is rapid enough to allow the selection of fiber mixes to provide uniform average fiber properties in a cotton manufacturing environment.

An effective quality improvement program should be based on four main foundations: (1) detection or monitoring, (2) proper analysis and interpretation, (3) immediate correction of mistakes, and (3) problem prevention. Current monitoring systems are used in the detection and correction phases, with the correction being applied at the instant of occurrence of the defect (e.g. re-piecing yarn ends after detecting a fault). In many situations, sensitivity and control limits, outside of which corrections are to be made, are selected randomly and without reference to the statistical nature of the monitored quality. This problem can lead to either over-control or under-control of the process with economical burdens associated with each. The areas lacking are the analysis and interpretation and problem prevention. Without a fault prevention program, continuous monitoring becomes an economically questionable tool because of the high cost of monitoring systems and the fact that the process of detection and correction are always be at the expense of running efficiency.

The use of continuously monitored data provides certain opportunities and challenges. It:

1. eliminates the concern for adequate numbers of tests,
2. introduces the complications of autocorrelation,
3. requires excessive computer memory for storing and analyzing large amounts of data,
4. provides opportunity for additional analysis to investigate the contribution of short term periodicities to product variability,
5. provides the opportunity to identify the sources of periodic variation and eliminate them,
6. provides the opportunity for determining how periodicities in one process contribute to the variability of subsequent processes and material, and
7. provides data which may be useful in simulation of the process.

Objectives

The overall objective of this work is to evaluate the procedures which can be used to analyze continuously monitored process data and to establish how the analyses should be used for process improvement.

Specific objectives include:

1. To construct an array of sensors and high speed data acquisition hardware to allow continuous monitoring of the significant material related variables in spinning,
2. To analyze the test results from the sensors by a variety of signal analysis techniques,
3. To establish a standard sequence of analysis techniques to use on continuously acquired data,
4. To attempt a new yarn modeling approach using the continuously monitored mass and tension variables in the model.
5. To integrate continuously monitored data into SPC procedure,
6. To determine currently available data which could benefit from the new analysis approach.

Experimental Work

Previous work has concentrated on:

1. installation of hardware for continuous monitoring of sliver and yarn size and spinning tension,
2. collection and storage of data from the three sensors
3. selection of analysis software for evaluation, and
4. developing an understanding of time series analysis

The last year has been devoted to evaluation and interpretation of analyses performed on a number of continuously monitored spinning trials. Normal running conditions were monitored as a control, as well as conditions of natural breaks, forced periodicities, and stressed conditions (approaching the spinning limit). The analyses tried include Box-Jenkins, standard Fourier transform signal analysis, and a variation of linear least squares analysis.

The Box-Jenkins approach developed originally in economic predictions. The analysis identifies a component of the variation, removes it, and analyzes the residuals for other components. This is done first for trends in the data and subsequently for periodicities. Ultimately the method assumes that the current values in the series (of the residuals) are related to previous values by a particular model (autoregressive or moving average, AR or MA) or combination of models (ARIMA). Then the model components are removed from the variation. The modeling procedure is considered a success when the residuals approach white noise. The approach is appears to be computationally intensive, lengthy in its iteration requirements, and somewhat subjective in its selection of a particular model (Figure 1). It is considered unlikely that the approach will be simple enough to "cook book" into a quality control system. It may find some application in quality research where scientists and engineers try to redesign a process. The cross correlation between two variables, which is a necessary consideration in relating input variables to output variables, is exceedingly complex in a Box-Jenkins analysis.

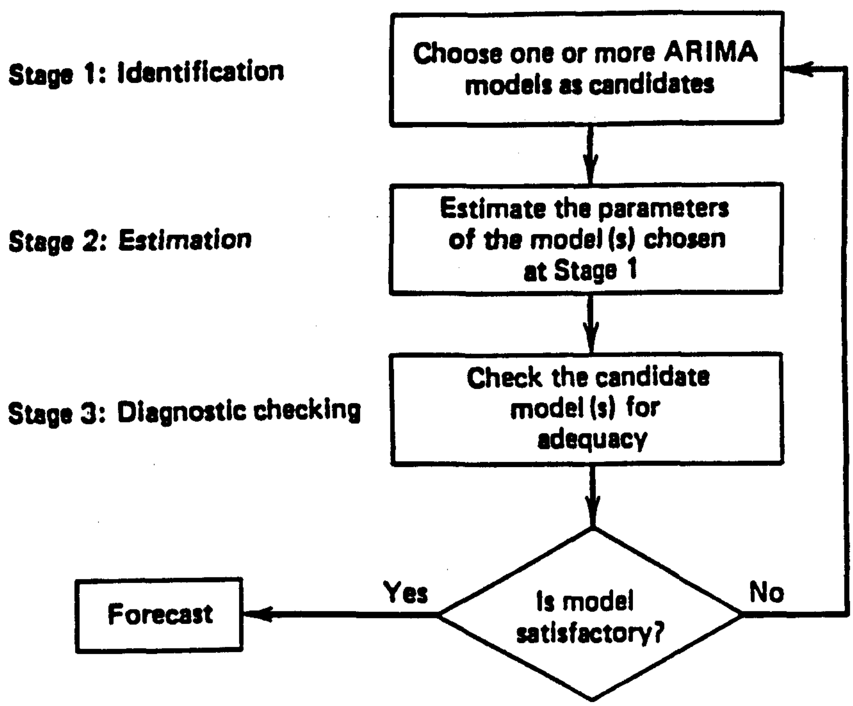

Figure 1 The Univariate Box-Jenkins Approach to Model Building

Fourier analysis assumes that a time series signal may be represented as a sum of sine and cosine terms. As such, the Fourier transform signal analysis approach is designed to reveal periodic variation in the continuous data stream. The method assumes that an input perturbation of the system will result in an output perturbation which may be damped, and shifted in phase, but retains the frequency of the input. Each data stream is sampled and analyzed independently and one looks for similarities in the frequency domain as well as frequencies related to machine parameters. Nonperiodic variations also give distinctive responses which can sometimes be recognized but the interpretation of such variations in terms of frequency is limited. One must be aware that the sampling frequency must be appropriate to the variation frequency or artifacts and mis-interpretation of results is likely. The desirability of converting the frequency domain into a spatial domain (velocity * frequency) is being considered. The signal analysis procedure is less computer intensive and more straight forward in application than the Box Jenkins approach. One can envision some sort of quality control application for this procedure. This analysis is being performed on the computer software, DADISP

The inclusion of a second variable by the calculation of a cross correlation time series is also possible. This allows the relationship between two variables to be determined.

A third approach makes use of linear least squares regression and matrix algebra to determine the relationships between variables. In our experiments, one might assume that the yarn size was directly related to roving size. By applying this model over a wide range of time lags, one can discern what the appropriate time lag is between the input and output. The approach is shown schematically in Figure 2. The appropriate delay is taken to be that which produces a minimum in the error sum of squares (Figure 3). A cutoff frequency must be applied to avoid misinterpretation and then the model developed can be used to predict the output variable from the input variable. The procedure is shown schematically in Figure 4 and an example of the prediction capability is shown in Figure 5. The results seem reasonable in predicting trends, but considerable random noise is apparent in the actual signal which is not predicted by the model. The matrix/least squares approach is done on the Matlab computer software, and while the procedures are of moderate computational requirements, most technical people have some appreciation for the process. The approach appears to be less subjective in its application than Box-Jenkins.

Conclusions

The tasks remaining are to select which of these techniques will provide the best and simplest analysis capability, to describe the procedures in language that others can follow and to test the approach on some process data from a production environment.

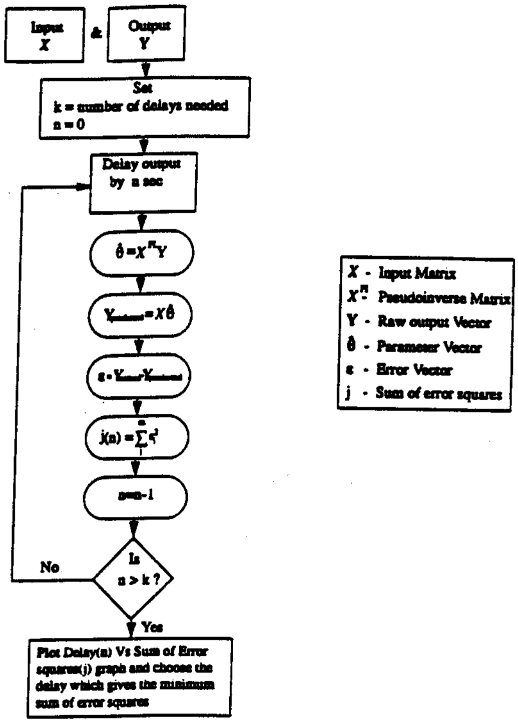

Figure 2 Schematic of the Linear Least Squares/Matrix Approach for Determination of System Time Delay or Lag

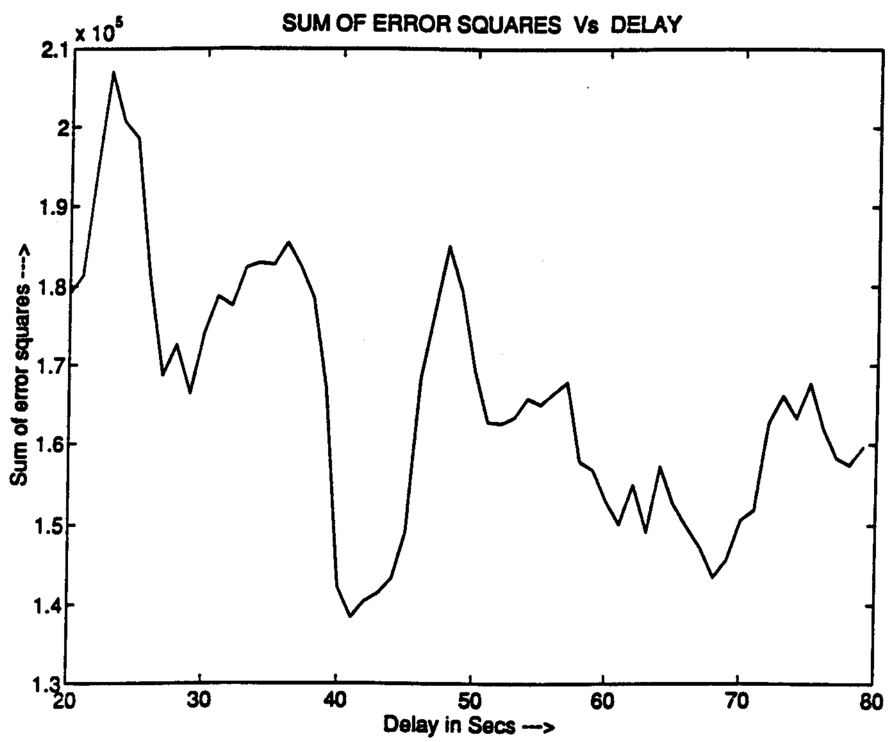

Figure 3 Determination of Appropriate Time Delay

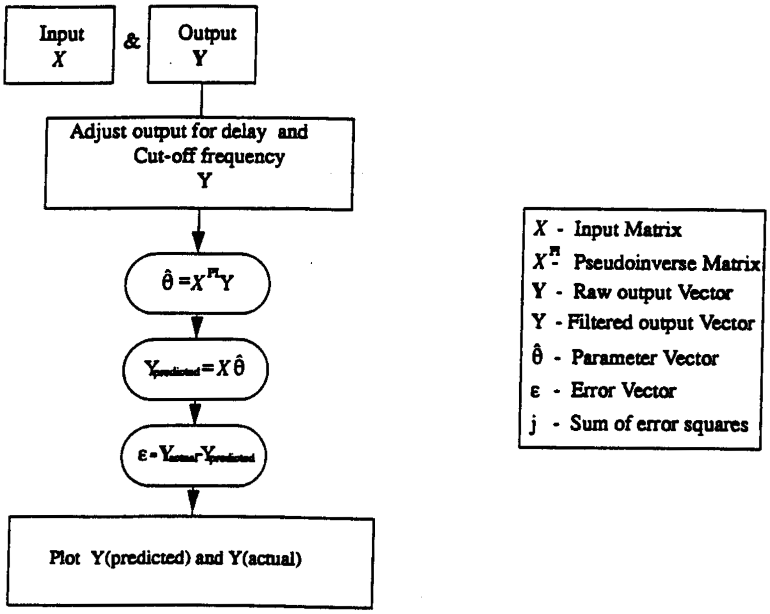

Figure 4 Schematic Description of Prediction Procedure

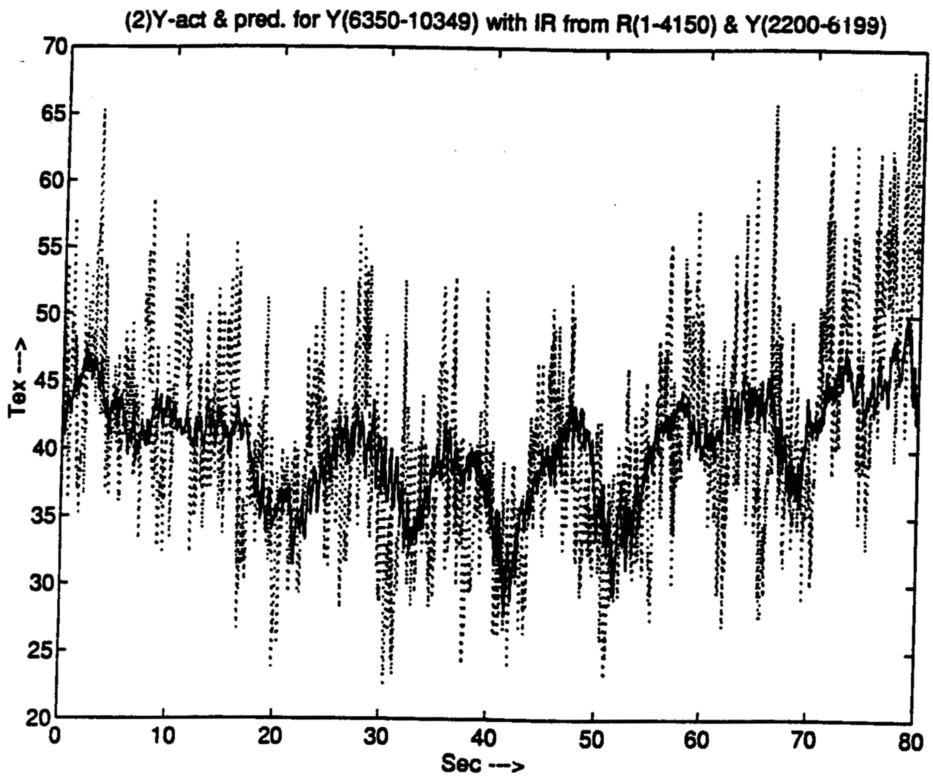

Figure 5 Actual vs Predicted Yarn Size (Solid line= predicted, Dotted line = actual)