A real-time information system for multivariate statistical process control

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Abstract:
Statistical process control (SPC) is widely used in process industries to monitor variations in process attributes. Typically, automatic devices capture a multitude of measurements on process and product characteristics every few seconds. Operators and engineers commonly monitor only a small subset of these. Multivariate SPC has been proposed to fully utilize the available data, however, interpretation of multivariate information is often too complex for most line operators. This paper describes the design and implementation of a real-time multivariate process control system that features a graphical user interface (GUI) and provides useful information for both line operators and engineers. The information system described in this paper should provide large-scale manufacturers with better access to information for identifying opportunities in continuing to improve processes performance and business competitiveness.
Keywords: Multivariate statistical process control; Real-time system; Continuous processes; Graphical user interface

Article:
1. Introduction
The last decade has produced dramatic changes in the way businesses operate and more changes are anticipated at the beginning of the 21st century. To meet the challenges of the new business environment, organizations have embarked on a number of initiatives, such as just-in-time, Six Sigma, enterprise resource planning, supply chain management, and e-commerce. Information technology (IT) is a critical component in the success of these and other initiatives by providing the means to gather data, provide analytical support and deliver information where it is needed in a timely manner. Successful integration of IT with core business operations is critical and can be a source of competitive advantage. While operations provide products and services, IT provides the information needed to operate, control, and improve processes, products, services, and business performance.

Many organizations have achieved significant improvements in business performance by utilizing an approach to quality, such as Six Sigma [1]. Popularized by Motorola and General Electric, Six Sigma is a systematic approach to data collection and statistical analysis to pinpoint sources of errors and ways of eliminating them. Six Sigma is an organization wide effort involves customers, operations personnel, engineers, management, and others to identify ways to add value for both the company and its customers. Manufacturing organizations, in particular, have utilized statistical process control (SPC) as a formal way to monitor and control process and product characteristics. SPC is often applied by constructing separate control charts of product quality characteristics or operational process characteristics that are used as independent indicators of process performance. An unusual pattern in one of these charts signals an assignable cause of variation. This approach is deficient since the observations of multiple process, or product, characteristics are assumed unrelated. In addition, the reliance on a small set of “favorite” variables ignores numerous process characteristics available from on-line data collection devices and does not fully utilize the available information. Multivariate methods are alternatives that incorporate the interdependence and volume of process characteristics. Until recent years, the application of multivariate methods for control charts were restricted and the results of multivariate methods suffered from the lack of effective presentation to allow for easy interpretation by operators and process engineers. Implementation of multivariate methods should provide operators with a mechanism for rapid identification of errors and suggest their causes to enable informed corrective action. Further, information systems to analyze multivariate data and deliver information about process characteristics are now more widely available.

This paper describes the design and development of a prototype for a real-time process control system based on multivariate SPC. Multivariate methods, specifically principal component analysis (PCA), are used to develop models of the steady-state operations of a manufacturing process. These models are used as a reference to monitor process performance and product characteristics. The system operates in real-time using data that is collected directly from the manufacturing process as it operates. This process data is analyzed using multivariate methods with reference to models of steady-state operation of the process. Operators and process engineers are informed of error conditions in the process and are presented with contribution plots that identify components of the manufacturing process making significant contribution to the observed variance in the process. The system presents this information using a graphical user interface (GUI) that was designed and developed to allow operators to interact with the system, and easily comprehend the results of this complex analysis for making decisions about the manufacturing process.

In the following sections, we first describe the quality control environment and the requirements of systems support for decision-making in this context. We outline the characteristics of the process control problem and use them to extract a set of desirable characteristics of process control systems. This provides a framework for the application of the real time process control system outlined in this paper. The review of the literature focuses on SPC and multivariate SPC, and investigates the application of some advanced methods to process control problems, including expert systems and artificial neural networks. Some background information for the application of our real-time information system is provided preceding the presentation of the model for our system with a detailed description of the components of the model, their implementation and role in providing an effective information system for process control. The paper concludes with a summary and some limitations and directions for future research.

2. Quality control environment

Quality control problems occur when the quality of the final product is not within established acceptable parameters defined for normal operation. In these situations, decisions need to be made regarding the identification of the problem, discovery of the causes of the problem and the selection of a requisite course of action to solve the problem. Decision-making in process control problem involves the following activities:

(i) Accurate detection of errors in the process.

(ii) Identification of possible causes of errors.

(iii) Analytical support for selection of a course of action to correct errors.

(iv) Adherence to the temporal bounds of the problem context.

Data from modern manufacturing environments contain many complex relationships due to the multiple processes that raw materials are subjected to in creating the final product. This complexity is compounded by the fact that IT used in manufacturing process industries allow for multiple data points to be collected and stored at frequent intervals in manufacturing data repositories creating large volumes of data. To be effective, any set of models that improves the understanding of the problem domain must be sophisticated and realistic enough to take into account the complex relationships within the data and incorporate them in the detection of errors in the process and the identification of their possible causes. Information systems that incorporate these models must provide the user with analytical support to explore the alternatives and their respective outcomes. If errors are identified in the manufacturing processes, they need to be corrected as soon as possible to avoid waste and consequent financial losses. There is a practical temporal bound to decision-making regarding potential courses of action to take when errors occur in a production line. Typically, losses in time lead to wasted products, which increase expenses. An ideal system would incorporate early warning mechanisms to warn operators of imminent failures in the system so that action could be taken to pre-empt such situations. Systems support for process control requires the following:

(i) Use sophisticated models that accurately model the environment.

(ii) Detect errors in the process.

(iii) Provide warning of failures.

(iv) Provide understandable presentation of results and outcomes.

(v) Work within the temporal bounds of the problem domain.

The temporal bound of the problem domain is a practical consideration in manufacturing processes control. A real-time system can be viewed as a conventional system with temporal bounds, the violations of which may invalidate operational consistency requirements. Real-time systems require more speed, interrupt scheduling, and prioritization as compared to conventional processes. This research uses a realistic definition of the temporal bound for the real-time requirement of the system noting that a stricter definition would require virtually instantaneous response times, which may not be required. This requirement is pragmatic in the context of manufacturing environments where faster response times can directly translate to smaller quantities of wasted, out of specification, products and less waste for the company. Real-time control systems have been a challenging and potentially useful area of research in process control.

Statistical process control tries to achieve quality by examining product characteristics and the association of these measures to the process characteristics. The intent is to identify sources of variation in the process for conformance of the final product to established standards of quality. While SPC is widely used as a tool for monitoring variation in process characteristics, the typical application often falls short of its potential. Operating characteristics that are known, or believed, to have a significant impact on quality are chosen from various stages of the manufacturing process. This allows for a manageable subset of the process data to be viewed with control charts. The selection of this subset is done as part of the design of the quality control policy using expert opinion of process engineers and research and technology groups in the organization [2]. SPC is often applied by constructing separate control charts for each of the “favorite” variables. These charts are used as independent indicators of process performance. An unusual pattern in one of these charts may be taken as a signal of a special, or assignable, cause of variation. SPC may be implemented by monitoring either product quality characteristics or operational process characteristics. In either case, the presence of special causes of variability is based on the information supplied by a small subset of the available data.

This traditional approach to SPC is deficient for at least two reasons. First, the reliance on a small subset of all variables ignores the multitude of process information that is available from the online data collection devices [3]. Second, observations of multiple process or product characteristics are assumed to be unrelated. Almost any measure of product quality is dependent on a sequence of preceding processes. Hence, measures of process characteristics are often correlated [4]. The manufacturing process is a continuous process that performs a series of sequential transformations to inputs to produce the final output. Outputs from one part of the production process become inputs to the next. At any intermediate stage of the process, the properties of the intermediate product are the net result of the transformations that are applied to it. This suggests a high level of interrelationships in such systems. These relationships play an integral part in decision-making activity that determines causes of errors and explores alternatives for their correction.

Multivariate methods take the interdependence and large volume of process characteristics into consideration. Multivariate SPC can be traced to Hotelling [5] and his T^2 procedure. Jackson [6–9] and Jackson and Morris

[10] extend Hotelling's procedure using principal components. Other contributors to the development of multivariate SPC methods include Alt [11–13] and Montgomery and Wadsworth [14]. Until recent years, multivariate methods for control charts were restricted to applications where the multivariate space was neither too large nor ill conditioned. In addition, most operators and engineers often view multivariate analysis as too complex for practical use. There has been significant progress on these issues in recent years. Multivariate control charts based on PCA and other methods have been shown to be useful for handling large, ill-conditioned data sets [15–19]. The results of PCA, however, are not very intuitive and do not always lend themselves to easy interpretation. To overcome this limitation, contribution plots are used for detecting the variable(s) that causes an out-of-control signal [20,21]. Kourti and McGregor [20] suggest a method that uses contribution plots to identify each variable's contribution to an out-of-control signal. "This approach is particularly applicable to large and ill-conditioned data sets" [22, p. 141]. PCA is well established as a useful multivariate model when, as in this environment, variables are auto-correlated due to the nature of the process and missing data points are often encountered as a result of the large number of variables and the unavoidable failure of data collection devices [4].

On-line instrumentation to capture process data and computer networks to assimilate the data into a database of process measurements are a preliminary requirement for multivariate SPC. Large modern manufacturing environments typically have these capabilities, whether for within the manufacturing environment or as part of an enterprise system. This is an important contribution of IT to process control. Process data is collected and delivered to sites that can assimilate all the information and update the control charts. Such an approach, that combines statistical and engineering process control, can provide an important tool for quality improvement [23]. IT can support the rapid identification of error sources using database query and retrieval techniques. Such techniques, however, involve a time delay for relevant data to be retrieved from the database, analyzed and processed for display. This delay is compounded when multiple sets of control limits must be maintained and multiple charts must be updated simultaneously. The inability to manage large amounts of data is often an obstacle to real-time updates of multiple control charts. More informative and intuitive graphical interfaces are needed to make the information presented by the control charts understandable for all operators and engineers. Multivariate SPC cannot become a practical tool for operators or process engineers until the results of methods such as PCA and contribution plots can be effectively presented and easily interpreted by operators and process engineers [4]. Specifically, the implementation of these procedures should provide operators with rapid identification of errors and which variable(s) caused an out-of-control signal [22, p. 141; 24, p. 126].

Object-oriented methods and simulation techniques have been evaluated by the process control researchers as alternative methods for effective process control. Object-oriented methods provide an effective approach for modeling the manufacturing process and incorporating the relationships between the entities of the system. The generated models are simpler and help the understanding, and hence the analysis of the system. Simulation methods recognize that process control systems are event-triggered systems that model and explain the relationships in the process and use these models to predict future behavior. Simulation models are typically theory-based and may not reflect real operating conditions. Thus, many critical nuances of the implementation of the manufacturing process may not be incorporated in the model [25]. Both object-oriented and simulation methods have considerable limitations in analyzing the massive volume of complex data inherent in manufacturing process data [26,27]. More effective methods are needed to analyze the large amounts of data from complex and continuous processes in order to determine the steps required to keep a process stable and to bring it back to stability when errors occur.

Expert systems and neural networks are techniques from the artificial intelligence area that have been applied to provide support for process control. Expert systems formalize the knowledge of domain experts and make this available to non-experts [28]. Expert systems are used to model the system and provide excellent analytical support. Their strength lies in their ability to explain the alternatives and decision choices. Models generated by expert system are usually rule-based and do not capture the nuances of the manufacturing system. Expert systems, by themselves, do not make effective process control systems [29]. Neural networks are very effective in developing models for non-linear systems that require the ability to handle noisy data. They are useful for manufacturing process data that typically contains noisy and missing data due to intermittent failures of collection devices. Neural networks can be used to provide effective process control with on-line, real-time data. The prediction capabilities of neural networks can be used to provide early warning of failures in the outputs of the system. Neural networks can be trained to build accurate, sophisticated, and dynamic models of the system. They are commonly used as embedded intelligent components for control loops of individual pieces of machinery and are rarely used for modeling the entire manufacturing process [30]. Neural Networks are typically a “black-box” approach and provide little support to help the user understand the process and fare poorly in providing analytical support and understandable representation of the system.

3. Model and implementation

The site for the development of the model is a large automated continuous manufacturing facility where automatic devices collect data on hundreds of variables across the product line every few seconds. Previously, the use of this data to monitor process characteristics consisted primarily of operators and engineers periodically checking a few “favorite” variables. Even though a database could capture selected data, query and retrieval involve a time delay for relevant data to be retrieved, processed and displayed. The size of the database and methods of access affect this time delay. The delay is further compounded when multiple control charts must be updated simultaneously and multiple charts must be examined to make decisions about process and product characteristics. A process control system based on multivariate analysis overcomes many of these inadequacies. PCA is used to reduce a large number of variables, representing process characteristics, to fewer dimensions. Contribution plots and a graphical user interface are used to provide operators and process engineers with multivariate process control results that are easily accessible and informative. The system as implemented in a single plant location has proven to be useful to production personnel for monitoring and controlling process operations. In the following section, we describe the development and implementation of the model for the on-line process control system. The model is based on an environment and conditions that typify many modern, large-scale manufacturing facilities with continuous processes.

The model for the system developed consists of three main components:

1. Data collection and storage.

2. Data analysis.

3. Graphical user interface.

A description of the manufacturing environment and overview of the model is included in the summary of the first component. The method of multivariate analysis is described in the data analysis component, and the features of graphical user interface follow.

3.1. Data collection and storage

The model assumes the existence of automated data collection devices that obtain data about process and product characteristics from the manufacturing operations at regular time intervals and deposit them into some form of a database for query and retrieval. Fig. 1 provides an illustration of the model developed. Data collected from the manufacturing process is deposited in the operations data log (database). Most modern automated manufacturing facilities have similar systems in operation. Typically, this data is used for monitoring process outcomes, including SPC control charts, for periodic reporting, and analysis of historical information.

In order to speed access to the data for the process control system, a direct link to the data capturing devices is used. A time slice of data is routed simultaneously to the data analysis component of the system and to the data log. The ability to bypass the database retrieval for data access reduces delays in data acquisition through query and provides real-time input to the data analysis component. The input of data on n variables at time t provides a snapshot of the entire system and is represented in Fig. 1 as a row matrix of size $(1 \times n)$, where n is the number of process variables captured at $t = 1$.

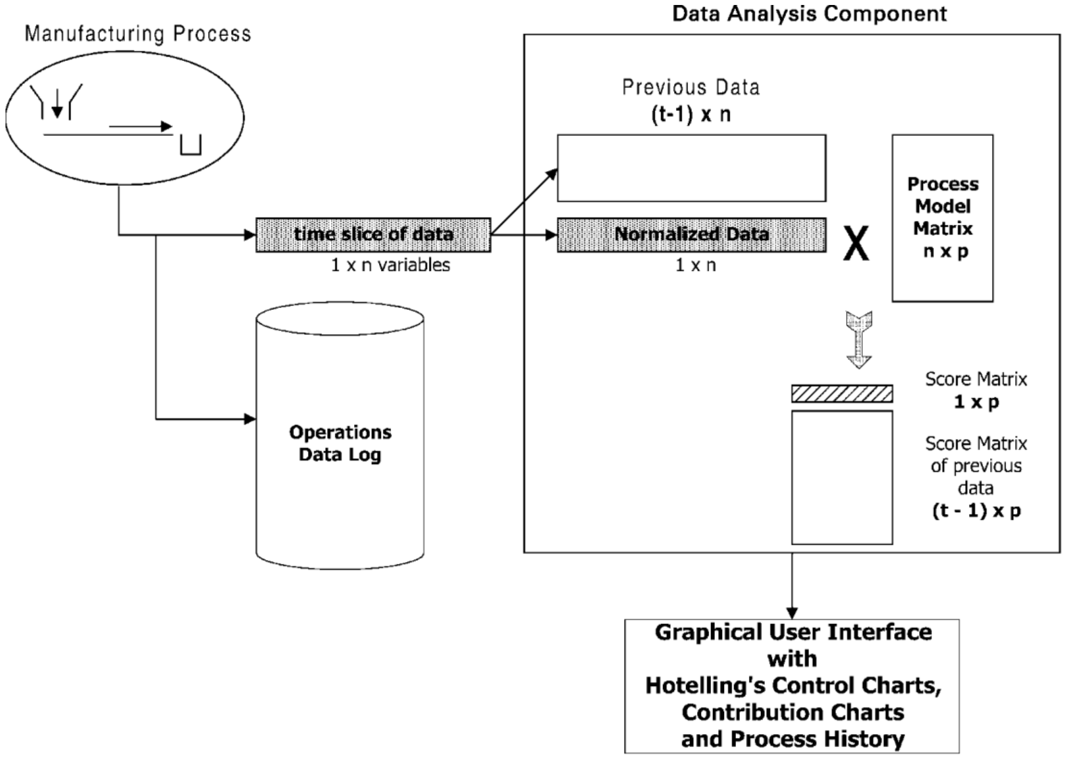

Fig. 1. Components of the real-time process control system.

3.2. Data analysis component

The data analysis component uses data from two sources: historical data representing the steady-state characteristics of process variables under normal conditions; and real-time data used as input for judging current operating characteristics. Interfaces with various data collection equipment send current snapshots of the process at the same time the data is sent to the operations data log. Analysis of data, updates to process control charts, and graphical displays are performed in this component. A buffer of the most recent snapshots of raw data is maintained in memory, rather than in storage, to allow for rapid updates and calculations. This design criterion imposes high memory requirements on the system, but the size of the buffer maintained can be manipulated based on available memory. The prototype was developed using a 60–120 minute fixed size, circular buffer. Thus the prototype system provided a history on the last couple of hours of operation of the process. The raw data is maintained to allow the users to view recent trends in process data (discussed in the GUI section below).

The raw process data is typically acquired from different parts of the manufacturing process and represent a variety of information about the process, such as temperature, power output, etc., for which the units of measurement vary greatly. Therefore, the data should be normalized prior to further analysis. If the data available for analysis consists of n observations of p variables, the raw data from the process is represented in Fig. 1 as a matrix of $n \times p$ values. The values of means and variance of the p variables used to normalize the real-time data were obtained from the steady-state operation of the process. This requires that two more vectors of the means and variances of the steady-state data must be maintained in current memory as part of the initialization of the system.

The creation of a model of the steady-state process is central to this system. The selection of data for developing steady-state characteristics is critical, as this forms the basis for future decisions on product quality. Data should be collected from times when product quality is acceptable. Data from multiple production runs is used to offset the variability attributed to a particular day. This data set is sufficiently large to capture typical process conditions and be statistically valid. Validation of data is achieved by comparisons with parameters for operating characteristics when acceptable product was produced. The goal is that this nominal data set should reflect the set of acceptable conditions for production.

To eliminate the effects of different measurement scales, the variables in the nominal data set are also normalized in the same way as described above for the real-time data. PCA is used with the resulting normalized nominal data set to obtain principal component scores. The principal component scores calculated from the nominal data matrix are identified in this paper, and shown in Fig. 1, as the process model matrix. A subset of all principal components is chosen to create the process model matrix. This subset is chosen based on the percentage of variability explained by successive principal components. The order of extraction is based on their ability to explain variability. The relative importance of the *i*th principal component is measured by the variance of that principal component as a ratio to the sum of the variance for all principal components. The first principal component extracted explains the largest proportion of variance, the second explains the next largest proportion, etc. Since the proportion of variance explained by successive principal components decreases, users may extract principal components until a certain proportion of explained variability is achieved. In the prototype system, principal components were extracted until at least 95% of the variability in the data was explained. Various rules have been developed for deciding when to stop extracting principal components. To provide flexibility, the system allows users to specify the desired proportion.

The next step is to use the normalized real-time data and the steady-state model of the process, to generate scores for the overall performance of the system. As shown in Fig. 1, the normalized real-time data is multiplied by the process model matrix to produce a vector of size equal to the number of principal components. In the traditional approach to multivariate SPC, the elements of this vector can be plotted against each other and compared against upper control limits. For two principal components, this creates an elliptical control region such that the points on the ellipse correspond to upper control limits [21]. Any point that falls within the ellipse represents an observation within the control limits. Points outside the control limits warrant further investigation. These may be investigated though contribution plots on principal component scores. Miller et al. [31] and MacGregor et al. [32] suggest calculating the contribution of each variable (in a principal component) to the principal component score. These variable contributions are plotted to provide a diagnostic tool to identify variables contributing to an out-of-control point [33]. This approach was used to develop the prototype system that features a graphical user interface and diagnostic tools.

Modern manufacturing facilities typically produce multiple products, each of which often differ significantly in both process and product characteristics. Many also have automated changeovers where controlling equipment change parameters of the manufacturing process and raw materials, to effect corresponding changes in product characteristics. In such cases, the measurements taken on a steady-state process significantly differ from one product to another. For such multi-grade product lines, data must be collected for each product and a steady-state model must be developed for each grade of the product.

3.3. Graphical user interface

This section describes a prototype designed and implemented at a large, automated, continuous, manufacturing facility. Some graphical user interfaces developed are shown with the information made available to users of the system. To develop the model, the entire process was divided into smaller sections and one section was used to test the prototype. Preliminary results from this system were encouraging and the model has been expanded to include the entire process. Experience indicates that benefits arise from maintaining the ability to analyze small sections of the process. Among the benefits are speed and processing efficiency, as well as the ability to examine in detail one part of a larger process. In large manufacturing processes, there are often sub-parts that have critical importance to the overall product quality and are often the targets of process control efforts. The system developed allows users the option of examining such critical sub-parts of the process or the entire process.

The initial interface for the user is shown in Fig. 2. The user begins by selecting the part of the process to be analyzed; the option “Entire Process,” as discussed above, is also available. Other options shown in Fig. 2 are not available until the user selects a process part for analysis. Once this selection is made, the default options for that part are loaded. These options include the number of principal components to be used (set here to the number of principal components required to explain 95% of variance). This interface requires the user to enter a product code for the product currently being produced. This requirement is subject to change as soon as the description of the current product code becomes available online. The “Reset Defaults” option selects defaults for the number of principal components and the number of data points to keep in current memory.

The menu option “Model Settings,” shown on the interface in Fig. 2, opens another dialogue to allow the user to select options for control limits and display settings for the control charts. The default settings that are taken for the model include, the number of principal components to be included, the number of variables in the model, the maximum allowable standard prediction error, and other settings used to establish limits for data plots, as illustrated in Fig. 3. On a cautionary note, the options on this screen assume that the user is familiar with the parameters for the control charts and the other charts that are generated. This is intended for use primarily by control engineers and should be protected as it may affect the behavior of the system.

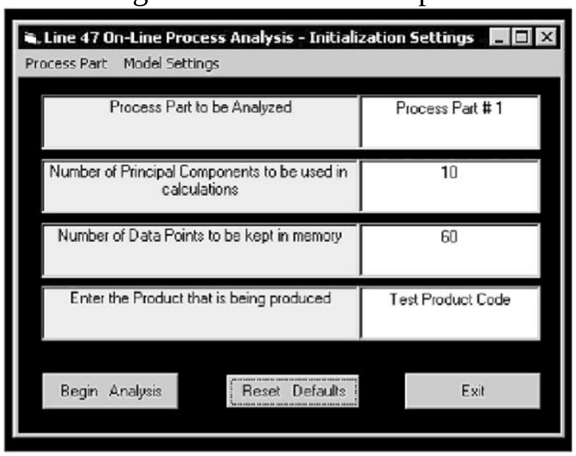

Fig. 2. Initial interface.

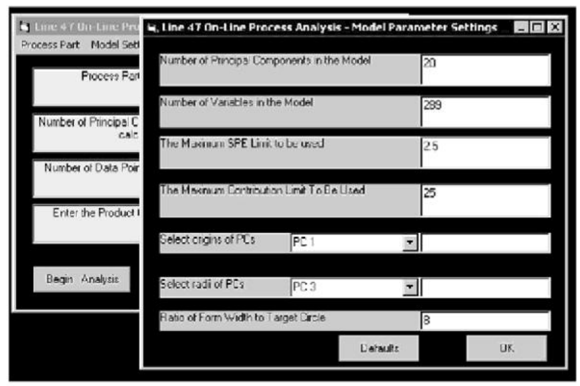

Fig. 3. Model parameter settings.

After the user has selected and confirmed the options for the control charts, the “Begin Analysis” control button becomes available for selection. This loads the process models and the means and standard deviations of the nominal data as benchmarks for analyzing current raw data. All variable names and their descriptions are also loaded at this time. The system establishes a real-time link with the data collection equipment and begins to collect data. We chose to implement the system with real-time data readings taken every minute. A combination of dynamic data exchange (DDE) and object-link embedding (OLE) were used to establish these links, using a DDE client and an OLE server. One possible technique is to use some data manipulation software such as Matlab® or Excel® to behave as the DDE client to the data collection equipment and as the OLE server for the real-time analysis software. Other techniques may be used, such as creating tags that serve as direct DDE clients to the data collection software. However, this technique increases the number of active DDE conversations, which has an adverse effect on the volume of network traffic and response time. Once the link with the data collection equipment is established, real-time monitoring of the manufacturing process may begin. In the initialization stages, the data buffers are empty, and the first few readings provide little information for detecting trends.

To initialize the system, two options are available:

(a) Use recent data (the previous hour) to establish a baseline

This option allows for the possibility that data could be from a different product. Such data may have process characteristics that are different from those expected by the process model. Thus, the model may report that the entire last hour of production was out-of-control. Newer incoming data shows better conformance to the model and tends to stabilize with the new parameters.

(b) Allow the system to collect a few minutes worth of data

Approximately 5–10 minutes of data will allow the system to work with data collected for the current product. In this case, there is a stabilization period while the system collects enough data to display trends. This period coincides with the manufacturing process stabilization that occurs for a product changeover to take place.

In developing the system, the second option was chosen because it corresponds with the characteristics of the manufacturing process more closely. There are advantages and disadvantages to each option, as discussed above, and one may be preferable in a particular environment.

Based on the techniques described in the data analysis component section above, the incoming data is normalized and multiplied by the model scores matrix, which produces a $1 \times p$ row matrix, where p is the number of principal components in the model. A data point for each principal component is plotted, as shown in Fig. 4. The ellipse depicts the target bounds that are computed based on Hotelling's T^2 statistic. One point on this "Target Plot" represents 1 minute of the system's composite performance. As new data is collected, this procedure is repeated for new data points and the plot is refreshed. The points on this plot are color-scaled so that the most recent plots have the brightest color and the older data points fade into the dark background. This is the primary interface presented to the users of this system. The data points are interpreted in the same way as the points on a single variable control chart. If the points fall within the ellipse, then the process is behaving correctly; otherwise an out-of-control condition has occurred and must be investigated. This is a two-dimensional plot with one principal component on the horizontal axis and another principal component on the vertical axis. The principal components used for the data points and the control limit ellipse, are identified in the labels and text boxes below the plot. The user may view plots of different principal components by selecting them on the control buttons.

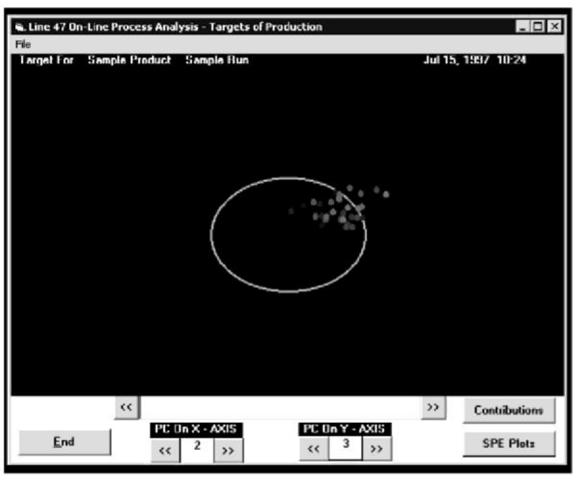

Fig. 4. Target and current production.

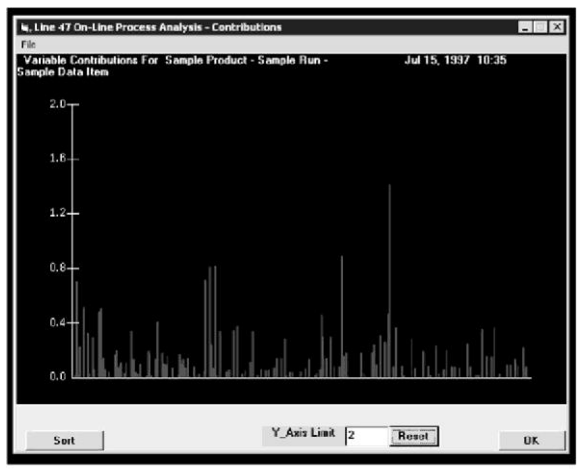

Fig. 5. Contribution plots for all variables at the current time.

As shown in Fig. 4, the user may view standard prediction error (SPE) plots and contribution plots. The SPE plots are calculated based on the differences between the actual incoming data and the data represented by the model. They provide information similar to that presented by the target plots. The SPE plots are presented as a line chart that is updated in real-time as new data arrives. By selecting the command button labeled "Contributions," the user is presented with a chart of the contribution of each variable to the variation in the process at that time. This interface is shown in Fig. 5.

From Fig. 5, the user gains a perception of the variables that contribute most to the variance. Typically, the sequence of the variables on this chart follows the sequence of the variables as they occur in the manufacturing process. A high degree of clustering at particular locations may reflect a localized occurrence of variance contributors in the process. Ideally, randomly scattered bars with small contribution magnitudes are desirable. This would imply that the errors are randomly scattered throughout the process and that there is little localized contribution of variance to the entire process. If variables from a certain region show up as high contributors, this is a good indication that a particular machine, or machine part, is the main contributor to the variance in the process. With a large number of variables, the chart in Fig. 5 may not clearly identify the major contributors to the variance. Thus, another option was incorporated to allow the variables to be sorted and displayed in order of their contribution to the variance in the process. Selecting the command button “Sort” generates a Pareto-like display of the top ten contributors to the variance in the process in descending order. Fig. 6 illustrates this display.

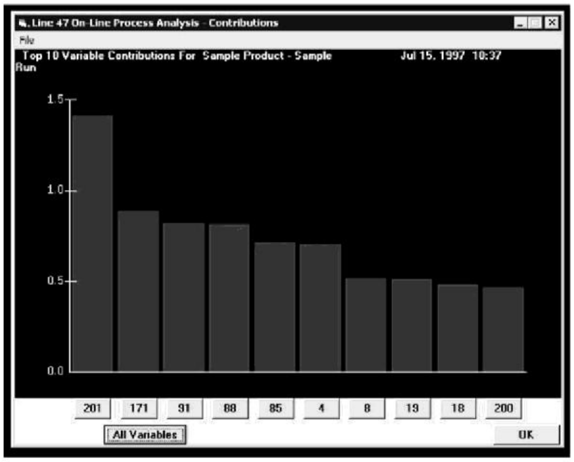

Fig. 6. Sorted contribution plots.

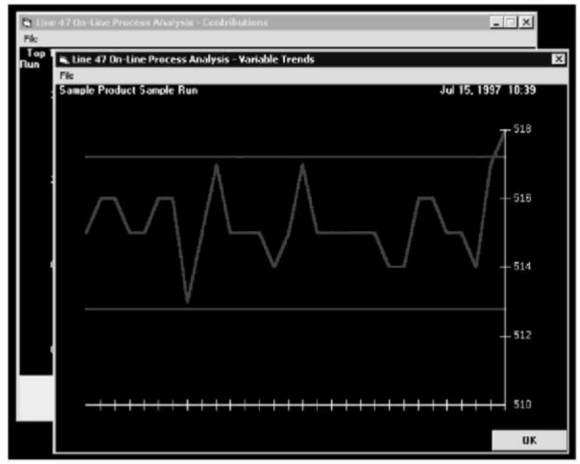

Fig. 7. Variable trend.

The chart in Fig.6 also identifies an index number, and command choice, for each variable displayed. Clicking on the button for a variable generates a time-ordered chart (or trend plot) for the variable, using the data currently available in the system (see Fig. 7). The display in Fig. 6 also allows the user an option to return to the chart in Fig. 5, by selecting the button “All Variables”. This would be required once the user has finished examining the primary contributors to variance and wants an overall view of the process. The horizontal lines in Fig.7 represent the acceptable range for this variable, as determined by the steady-state model. The user may return to the Fig. 6 display by selecting the “OK” button.

4. Conclusion

This series of easy to understand and intuitive displays captures the intricacies of the complex nature of the large manufacturing process. The user is presented with an information system that provides an accurate overall picture of the entire process with the ability to drill-down into details about individual measurements taken from the process. The process of identifying an in control state is as simple as checking to see whether the data point that represents the current state of the process is inside the target circle. The user does not have to understand any of the complex multivariate control charts and statistical calculations that create the interface. Further, if out-of-control signals are observed, the user may examine a series of other displays to identify the source of variation.

Initial runs of the prototype on both sub-parts of the process and on the entire process have been very encouraging. It was observed that the system was able to identify errors in the process at least as well as the existing SPC system that was previously in place. The system overcomes one of the major limitations in the existing SPC systems, which is lack of information on probable causes. A feature of an overall contribution plot, which was seen as major benefit by both process engineers and line operators, was the overall view of contributions of variance in the process. Often, the operators were able to identify possible malfunctions in machinery components from the region in which contributions to variance were high. The system, with minor modifications, was adopted by the manufacturing facility and is currently in use as one of their process control systems. The development and implementation of similar systems for other manufacturing environments should also prove beneficial.

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