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Development of an Innovative Managerial Control System: An Application to the Precast Concrete Building Products Industry

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Abstract
The monitoring of business processes and their variables has strategic importance in order to respond to today's dynamic business world. This paper introduces an ongoing research initiative, which is focussed on developing an innovative managerial control system to analyse historical and on-line information about business processes, establish relationships between internal and external business process variables and advise senior management on future decisions. Multivariate Statistical Process Control (MSPC) techniques, which have been applied in chemical and process industries to control process operations, are utilised to model, monitor and control business process variables of Precast Concrete Building Products industry. Through a detailed case study, this paper illustrates offline modelling of business process variables utilizing MSPC techniques such as Principal Component Analysis. Also, a methodology is discussed for the monitoring of business processes and dynamic feedback for corrective actions to managers if the business processes are found out of control.

Keywords
Business processes, MSPC, Control, Precast Concrete Products Industry

1. Introduction

A business process is influenced by two main streams of planning at managerial level: strategic planning, that guides the policies and future direction of the business organization and operational planning that is aimed at controlling processes for efficiency, quality and reliability of product or services. Strategic plans are often long term and take 'big picture' approach and look at what needs to be achieved often under broad strategic headings (Hale and Whitlam, 1997). The strategic plan identifies what is to be achieved from an operational or tactical plan. Strategic planners have to consider historical context and be able to anticipate how business processes may be in the future. Strategic planning considerations might include issues of economy, suppliers, technology, competitors, customers, socio-political factors, environment and issues of government. Execution of an operational plan will contribute towards the achievement of strategic plans. The internal factors that should be considered in operational planning are, amongst others, finance, employees, capital equipment, research and development, customer requirements, productivity, environmental laws, products and services.

Business processes handle complex tasks in ever-changing environments and need continual adaptation of strategy and decision criteria to be performed effectively (Fuglseth and Gronhaug, 1997). Therefore, the monitoring of business processes and their variables has strategic importance in order to respond to the current dynamic business world. This paper introduces an ongoing research project funded by Engineering and Physical Sciences Research Council, UK government, which is focused on developing an innovative managerial control system (IMCS) for Precast Concrete Building Products industry. The system analyzes historical and current information about business processes, establishes relationship between internal and external variables and advises senior management on future decisions. Multivariate statistical process control (MSPC) techniques, which have been applied in chemical and process industries to control process operations, are utilized to model business process variables and for their monitoring and control. Through a detailed case study in PCBP industry, this paper illustrates offline modeling of business process variables using MSPC techniques primarily Principal Component Analysis (PCA) for monitoring of business performance. The prediction of variables using Partial Least Squares (PLS) is not covered in this paper due to limitation of space and will be described in forth coming papers.

2 IMCS Framework, Components and Development

A business organization has enormous amount of data about their business processes. Efficient processing and analysis of the data is essential to depict relationships, trends and patterns between various variables. This is critical to an enterprise that desires to exploit operational and other available data in order to improve the quality of decision-making and gain critical competitive advantages (Ma et al., 2000). Examples of such analyses in businesses include identifying buying patterns of customers, detecting patterns of fraudulent credit card usage, extrapolating time series to anticipate future outcomes, etc.

MSPC and 3D-VR visualization techniques have been presented in this paper to identify relationships between the variables and to monitor and control business processes. The 3D-VR interactive data visualization approach supports a bottom-up approach to discover structure in the data set as a whole, which is interactive and requires human elements to identify patterns. The MSPC techniques use analytical approach to identify the process deviations, relationships between variables and forecasting.

Figure 1: Outline of the IMCS Framework

Figure 1 shows the overall process control approach used in IMCS, which consists of three main components: databases, Multivariate Statistical Business Process Control (MSBPC) and visualization. The objective of the databases is to store information and use it to derive process variable values. The databases store data for production, sales, inventory, material supply and distribution. The MSBPC component is developed utilizing MATLAB6.5, DB Toolbox (Mathworks, Inc.) and PLS_toolbox (Eigenvector Research, Inc). The DB toolbox provides functions for connecting to databases and PLS toolbox provides MSPC functions for MATLAB programming environment. Several functions and graphical user interfaces were written in MATLAB to develop an integrated IMCS. The output of MSPC analysis can be viewed in 2D and 3D Virtual Reality (VR) graphs. The business process variables are also visualized in 3D-VR. For VR interactive data visualization, a program was written in MATLAB, which generates an interactive information visualization model in VR using Virtual Reality Modeling Language 97(VRML97) and JavaScript programming. Marasini and Dawood (2003) provide details of visualization development.

3 Multivariate Statistical Business Process Control

The MSBPC component of IMCS utilizes MSPC techniques to monitor, control and predict business processes. The MSPC techniques are being used in chemical and manufacturing industries to monitor process performances and product characteristics. Some examples are Singh and Gilbreath, 2002; Gurden et al, 1998; MacGregor and Kourti, 1995; Wise and Gallagher, 1996. The objectives of MSPC include process monitoring to ensure overall production control, fault detection and diagnosis, determination of key process variables and the generation of inference models used to forecast and optimize product quality (Gurden et al., 1998). The rational of MSPC is to identify the combined relationship among the different variables, establish the control limits of the process variables and identify any shifts in the processes ensuring that the process is in control. PCA has been used to develop the business process model and monitor the process. Squared Prediction Error (SPE) and Hotelling's T^2 statistic are used to identify the shift of variables from the base line. The PLS technique is used for prediction of business process variable values based on input variable values. There are two main steps in MSPC: establishment of base line model and monitoring of new operational data to ascertain if control is maintained.

3.1 Development of base model using historical data

A leading UK manufacturer of precast concrete products was selected for the development and validation of IMCS. Several brainstorming sessions with financial, sales, production and distribution managers were conducted to identify an extensive list of process variables to study. The external variables affecting company business processes and the internal company variables related to the business processes such as marketing, financial, production and distribution were identified through process mapping. For demonstration purposes, marketing process variables were selected and modeled. The variables used include: Production, Stock, Marketing budget, House starts, Fuel prices, Interest Rate, Index of distribution, Sunshine (average hours), Rainfall, Index of production, Sales, Stock outs and construction order value. The values of the process variables for years 2000, 2001 and 2002 were used to develop a base model. Table 1 shows the data collected for the variables and their sample values.

Table 1: External and Internal Business Process Variables Base Data

Figure 2: Variance Captured by Principal Components

The first step in developing base model is to develop a raw PCA model with maximum number of PC's. The raw model consists of all PCs that will describe 100% variations in the data set. The variance captured by the principal components has been presented in figure 2. The first PC captures highest variance in the data; the successive PC's contribute to lower percentage of data variance. The first PC describes the systematic data variation and the last PC describes the stochastic data variation. Modeling higher percentage leads to fitting noise while a much lower percentage makes the PCA model less accurate (Santen et al., 1997). The base model to be used for process monitoring should therefore have minimum but sufficient number of principal components. Users can use some rules of thumb to select the number of principal components, which are: PC's that describe 90% of the data variation (Santen et al. 1997); PC's that describe 85% of the variance (Bissessur *et al.*, 1996); PC's that have Eigen Values greater than one (Petroni, 2000). One other approach to identify optimum number of principal components, used in PLS toolbox as well, is "cross validation method" (refer Jackson, 1991). Six principal components were selected in this example.

The base model consists of data about loadings (Fig. 3a for PC1), PC's scores (Fig. 3b for PC1), Hotelling's T^2 statistics (Fig. 4a) and SPE (Fig. 4b) with 95% and 99% confidence limits. The names corresponding to variable numbers on figure 4a can be seen from table 1. The graphs shown in figure 3 are available for all principal components considered for modeling. The data not within the 95% confidence level represent the process conditions deviating from the normal operating conditions. The observation of one variable such as Hotelling's T^2 allows focusing on abnormal events in the large number of measured variables. The inner dotted horizontal lines represent 95% (warning) and outer dotted lines represent 99% (action) limits. The loading vectors are the link between measured variables and principal components. The score vectors represent the co-ordinates of the data points projected on the principal components. Details on these statistical terms used in this paper can be found in Jackson, 1991.

99% Confidence limit
(Action Limit)

(a) (b)

Figure 3: Base Model Principal Component 1 (PC1) Values: a. Loadings b. Scores

95% Confidence limit
(Warning Limit)

99% Confidence limit
(Action Limit)

(a) (b)

Figure 4: Base Model Statistics a. Hotellings T^2 b. Residuals (SPE)

3.2 Monitoring of new operational data to ascertain if control is maintained

The values of the variables used in section 3.1 for months 1 to 6, year 2003 were used as new test data to monitor the business. The test data are projected to the base model and new loadings, PC scores, Hotelling'sT^2 statistics and SPE are obtained. A measure of variation within the PCA model is given by Hotelling's T^2 statistics (Fig. 5) and by monitoring T^2 statistics, the common cause of variation can be detected. New events can be detected by computing the SPE of residuals of the new observations (Fig. 6), which is denoted by Q in figure 7. Using PCA and Hotelling's T^2, the process seems on control. However, SPE chart shows that the test data sample #1 and #2 signal the out of control situation and the high SPE value indicates unusual events.

Figure 5: T^2 Chart for Test Data **Figure 6: Residual Chart for Test Data**

3.3 Interpreting the out-of-control signal

When the T^2 chart or SPE chart signal the presence of out of control situation, the next step is to identify which variables or combination of variables are causing it. The contribution plots corresponding to the out of control observation should be investigated. The contribution plots are the tools to identify components of the processes (manufacturing or business) making significant contribution to the observed variances in the process. The loadings indicate that which variables are important. The purpose of contribution plots is to suggest the investigator where to begin investigation and the contributions help interpret events that are identified as special causes by querying the underlying data.

From the contribution plots for the residual for test observations #1- January 2003 (Fig. 7a), it is clear that the variables causing the process variation outside the 99% confidence limit is due to change in crude oil price index and marketing budget. Similarly the contribution plots for the residual for test observation #2- February 2003 (Fig. 7b), the variables causing the process variation outside the 99% confidence limit is due to change in crude oil price index and stock out percent. The trend is that crude oil price is changing and has the highest contribution in residual values in observations #1and #2. Similar contribution plots can be plotted for a point, which is known to have moved outside the control limits and one within the control limits, the variables, which have experienced the greatest change, can be identified.

(a) **(b)**

Figure 7. Contribution Plot of Different Variables on Residuals for Obs. (a) #1 (b) #2 (Fig. 6)

3.4 Bringing the out-of-control business process to in-control state

The process of bringing back out-of-control business process to in-control state requires acting on internal variables that have high influence of variables causing out of control signal. Due to limitation of space, how managers can influence in bringing the out of control process to in-control could not be included in this paper.

4. Summary and Conclusions

A dynamic business process monitoring and control system, IMCS, was developed. The IMCS utilizes principal component analysis and partial least squares techniques in monitoring and controlling business processes and prediction of the business process variables. The system supports knowledge discovery in managing business processes. The methodology used in IMCS to control the business processes was demonstrated using a case study in Precast Concrete Industry. The system was presented to the industrial business managers and they have regarded the system as beneficial to the industry. Further experimentation and development of IMCS is being carried out to identify more internal variables that managers can influence to control the business processes. It is envisaged that IMCS will be applicable to construction industry such as monitoring production of construction site operations.

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