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A methodology for monitoring system performance

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Monitoring and improving manufacturing processes involves identifying, investigating and eliminating problems responsible for inefficiencies in production operations. While statistical process control tools, such as control charts, are available for process monitoring at the operational level, methods for evaluating system performance from more strategic and tactical levels are limited. The traditional control charts that monitor a single process parameter at a time may not be appropriate in situations where interrelationships among various system measures exist. Although multivariate process control techniques allow for simultaneous monitoring of several process parameters, they require assumptions of independence and multivariate normality of data. In addition, their application has mostly been at an operational level. In order to assist managers in monitoring and improving manufacturing system performance, this paper proposes an individual control chart that monitors an integrated performance index generated from a non-parametric method, which effectively considers multiple performance measures and the relationships between them. The primary advantages of this method are that a single integrated measure can be monitored, does not require assumptions of independence and multivariate normality of data, and allows for the integration of decision-maker's input when the system measures that are monitored have unequal importance.

1. Introduction

Performance monitoring and improvement of manufacturing systems have received significant interest in academia and industry. While practitioners are implementing methods to improve manufacturing operations in order to respond quickly and effectively to customer needs, researchers are emphasizing the development of new and more effective methods that can be applied to industry problems. The primary goals of manufacturing system monitoring are to identify, investigate and eliminate problems that are responsible for inefficiencies in the production operations.

A manufacturing system can be defined as an activity that transforms inputs to outputs. In production operations, resources such as raw materials, capital, labour and machines are considered as inputs. Outputs are the actual number of products produced and/or system performance measures, such as throughput rates (number of units produced per unit of time), work-in-process levels (inventory levels generated), and defective rates.

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Managing any business operation, manufacturing or otherwise, requires performance measures. This has become a truism in managing operations ever since the total quality revolution of the past few decades, where 'you can't manage what you can't measure' has become a battle cry of most quality gurus. The evaluation and use of multiple performance measures has also been promoted by most of the performance measurement literature from such areas as operations, engineering, and cost accounting (e.g. Kaplan and Norton 1996, Nanni *et al.* 1992, Adams *et al.* 1995). These measures also need to have various characteristics, including strategic and operational dimensions, for consideration. Yet, when a number of performance measures are to be evaluated simultaneously, managers may not be able to discern easily when a particular process is performing well or not.

This paper proposes a methodology for effectively monitoring manufacturing system performance in the presence of multiple input and output performance measures. The motivation for this research stems from the fact that few methods that integrate management preferences with performance data currently exist for evaluating and monitoring system performance from a strategic/tactical standpoint. While existing methods, such as control charts, can effectively be utilized for monitoring individual and multiple process parameters, their application is primarily at an operational and disaggregate level. In addition, the traditional control charts limit themselves to monitoring a single process parameter and multivariate charts, which allow for simultaneous monitoring of several process parameters, require assumptions of independence and multivariate normality of data. These issues are further amplified in evaluating system performance where several parameters and relationships among them exist. Also, from a strategic/tactical standpoint, some system parameters may be more important than others and depend on the competitive priorities and goals set by companies. Thus, it is critical to develop a methodology that effectively addresses these issues and provides management with a tool for system performance monitoring and improvement.

2. Literature review

A number of reviews on the practice, requirements design and development of performance measurement systems exist (e.g. Adams *et al.* 1995, Lockamy and Cox 1994, Neely *et al.* 1995). Kueng (2000) points out two important characteristics for performance measures that we seek to address here.

- Performance is multidimensional. As performance has many contributing factors, it cannot be gathered and assessed by a single indicator.
- Performance indicators are not independent. Most performance indicators stand in a relationship with one another. For the most part, the type of relationship is either conflicting or complementary; independence is the exception rather than the rule.

Several techniques have been proposed in the literature for process improvement and control at various levels of decision making and management. At the strategic level of analysis, performance measures range from standard financial measures, such as return on assets or investment (ROA and ROI), to stock market returns. One of the most popular evaluation techniques at the strategic level of performance is Kaplan and Norton's (1996) Balanced Scorecard approach. This approach is a strategic management instrument that supplements traditional financial measures with three additional perspectives: the customer, the internal business process, and the learning and growth perspective. It is meant to be a tool for describing an organization's overall performance across a number of measures on a regular basis and is focused on corporations or organizational units, such as strategic business units, but not on business processes. It involves business processes only as far as their impact on customer satisfaction and in achieving an organization's financial objectives.

Some of the tactical level performance evaluation methods that consider multiple dimensions from a quantitative modelling focus include Bititci *et al*. (2001), Ghalayini, *et al*. (1997), Sabri and Beamon (2000), Sarkis and Talluri (1996), and Suwigno *et al*. (2000). Yet these techniques do not simultaneously consider a multi-factor, multi-period environment from a continuous process monitoring standpoint and fail to address issues relating to managerial preferences in system performance evaluation. In addition, these methods do not provide for a mechanism that alerts managers to when the system performance falls below certain standards. The approach proposed in this paper effectively addresses these issues.

At the operational level, some of the important performance evaluation tools are Pareto charts, process charts, cause-and-effect diagrams and control charts. Although Pareto charts and cause-and-effect diagrams are useful for investigating and eliminating defects, these methods do not allow for continuous process monitoring. While control charts can effectively be utilized at an operational level, their applicability for system performance monitoring is limited due to the issues addressed in the previous section. Since the methodology utilized in our paper draws from some of the concepts in multivariate process monitoring, we provide a review of these techniques and relate them to our research.

Since research in the area of multivariate process control is fairly broad, we only address some of the relevant work. For detailed reviews on multivariate process control techniques, see Alt (1984), Jackson (1985), Lowry and Montgomery (1995) and Wierda (1994). Hotelling T^2-charts, Multivariate Shewhart charts, MCUSUM (Multivariate Cumulative Sum) charts, and MEWMA (Multivariate Exponentially Weighted Moving Average) charts are some of the widely known techniques.

The applicability of multivariate statistical techniques to monitoring system performance is primarily limited due to the assumptions of independence and multivariate normality of data. Since production system parameters and product characteristics are usually correlated, it may be difficult to satisfy these assumptions. Jackson (1985) proposes a method that involves transforming the original process parameters into principle components and using these orthogonal variables to develop control charts. Although this method achieves independence, it may result in loss of information about the original variables, and also poses difficulty in interpreting the principle components. In the presence of highly correlated parameters one can individually monitor all of them separately (Woodal and Ncube, 1985). However, this method can be quite cumbersome since it may require tracking of many variables separately.

MCUSUM and MEWMA charts are multivariate versions of univariate CUSUM and EWMA charts. They basically utilize weighted sequences of prior observations. The decision-maker provides the λ value, which is the weighting constant. The MEWMA charts weigh past observations in the same manner for all the quality characteristics. In situations where the monitored variables are of unequal importance, the regression-adjusted method proposed by Hawkins (1991) can be utilized. However, this method requires all the regression-based statistical and data characteristic assumptions.

This paper considers the above-mentioned characteristics of traditional multivariate statistical techniques and develops a methodology for effectively monitoring system performance. It overcomes limitations such as independence, multivariate normality of data, and unequal importance of variables as discussed below. The proposed methodology allows for consideration of variables that are correlated (process inputs and outputs). It simultaneously considers inputs and outputs in deriving a measure for the system efficiency, which is based on a non-parametric method referred to as Data Envelopment Analysis (DEA). Thus, we do not need assumptions of multivariate normality of data. It allows for incorporation of decision-maker preferences when the variables that are measured have unequal managerial importance. This is achieved through the utilization of the Analytical Network Process (ANP) for obtaining relative importance weights for variables that are measured. These weights are integrated into the DEA evaluations in obtaining the system efficiency. The system efficiency scores evaluated over time are monitored using an individual control chart.

3. Methods

This section provides a brief introduction to the methods used in this paper: the ANP, DEA and individual control charts. For more details on these methods, please see the indicated references.

3.1. *The Analytical Network Process*

The first step in our methodology is to determine the managerial 'importance' levels or 'preferences' for the performance criteria that will be used to evaluate the efficiency of the manufacturing process. The proposed method to integrate managerial preferences into the development of the control chart is the Analytical Network Process (ANP), a multi-attribute decision making model (Saaty 1996). The relative importance weights of the various decision-makers elicited from ANP can be used to determine the bounds of the weights for the factors. The bounds can be determined by using the highest and lowest weightings from each decision-maker for each factor, or could be based on the standard deviation of the factors from the decision-maker weights. In this paper, we will simply use the highest and lowest weights for each factor as bounds. For additional insights into the application of the ANP method, see Azhar and Leung (1993), Hamalainen and Seppalainen (1986), Meade *et al.* (1997), Saaty (1996), Saaty and Takizawa (1986) and Sarkis (1998).

3.2. *Data Envelopment Analysis*

Productivity models have traditionally been used to evaluate efficiencies of systems. Data Envelopment Analysis (DEA) models measure the efficiencies of a set of homogenous systems or decision making units (DMUs) by incorporating multiple input and output factors. The efficiency is defined as the ratio of weighted outputs to weighted inputs.

Several DEA models exist in the literature for analysing various problem environments. Many of these models are extensions of the basic ratio DEA model proposed by Charnes *et al.* (1978), which is also referred to as the CCR (Charnes, Cooper and Rhodes) model. In this paper, we use one such extension proposed by

Andersen and Petersen (1993), which allows for effective ranking of DMUs. Their model is shown as formulation (1) below:

$$
\begin{aligned}
\max \quad & \sum_{r=1}^{s} v_r y_{rp} \\
\text{s.t.} \quad & \sum_{i=1}^{m} u_i x_{ip} = 1 \\
& \sum_{r=1}^{s} v_r y_{rj} - \sum_{i=1}^{m} u_i x_{ij} \leq 0 \qquad \forall j \neq p \\
& v_r, u_i \geq 0,
\end{aligned}
\tag{1}
$$

where

x_{ij} is the observed value of input i for DMU j,
y_{rj} is the observed value of output r for DMU j,
x_{ip}, y_{rp} are the inputs and outputs of DMU 'p' whose efficiency is under evaluation,
v_r is the weight attached to output r,
u_i is the weight attached to input i,
s is the represents the number of outputs,
m is the represents the number of inputs.

Formulation (1), which we refer to as the 'ranking' CCR (RCCR) model, allows for efficiency scores to be greater than 1, thus providing for an effective ranking of DMUs, which is one of the limitations of the CCR model. The above model is run n times in evaluating the efficiency scores of all the units, where n represents the number of DMUs.

3.2.1. *Integrating managerial preferences into the RCCR model*

Constraining the range of input and output weights (u and v) provides a method for integrating managerial preferences into the RCCR model. The use of assurance regions (AR) for restriction of weights is one approach that allows for the incorporation of decision-maker's preferences into DEA evaluations. Thompson *et al.* (1990) describe the concept and derivation of ARs. The process of setting AR begins by defining upper and lower bounds (UB and LB) for each input and output weight. The bounds for each factor weight allow for defining constraints that reflect the relative preferences of various factors. These LB and UB values may be represented as ranges of preference weights for each of the factors as defined by the decision-makers. The AR constraints relate the weights and their bounds to each other. The generalized AR constraint sets that are derived from LB and UB data are:

$$
v_i \geq \frac{\mathrm{LB}_i}{\mathrm{UB}_j} v_j \quad \text{and} \quad v_i \leq \frac{\mathrm{UB}_i}{\mathrm{LB}_j} v_j. \tag{2}
$$

These constraints can be added to formulation (1) to form the RCCR with assurance regions (RCCR/AR) model. The critical process variables (performance criteria) form the set of inputs and outputs for the RCCR/AR model. The lower and upper bounds of the input and output weights (critical process variable weights) are determined by evaluating the relative importance weights from the ANP process. This is detailed further in the illustrative application.

3.3. *Individual control charts*

The DEA and ANP models are utilized to evaluate the performance of the process over time. In order to track and monitor the performance, a control chart and appropriate calculations for a sample size of 1 are required. This is because DEA provides a single efficiency score for each time period that represents the process performance.

When the sample size for process control is $n = 1$, an individual control chart, referred to as the x-chart, can be utilized for process monitoring. For more information on the applicability of these charts, refer to Evans and Lindsay (1999). The Upper Control Limit (UCL) and the Lower Control Limit (LCL) for an x-chart are:

$$\mathrm{UCL}_x = \bar{x} + \frac{3\bar{R}}{d_2} \tag{3}$$

$$\mathrm{LCL}_x = \bar{x} - \frac{3\bar{R}}{d_2} \tag{4}$$

where: $\bar{x}$ is the sample mean; $\bar{R}$ is the mean sample range; d_2 is the table value obtained from standard quality control tables.

Since there is not enough information to derive a measure for variability from a sample size of 1, a moving average of ranges of n successive observations is recommended. For example, a moving range for $n = 2$ is calculated by finding the absolute difference between two successive observations. The number of observations utilized in the moving range determines the value of d_2, which is obtained from standard quality control tables. The control limits for the moving range chart are defined by:

$$\mathrm{UCL}_x = D_4\bar{R} \tag{5}$$

$$\mathrm{LCL}_x = D_3\bar{R} \tag{6}$$

where: D values are obtained from standard quality control tables; $\bar{R}$ is the mean sample range.

4. Monitoring system performance

Our methodology involves the application of a series of models. Initially, the critical process variables and the relative importance levels are identified through the ANP process. Simulated process data are generated for the example, and process efficiency is evaluated by utilizing the RCCR/AR model with AR restrictions identified from the ANP method. The individual control charts are then generated and the process performance is monitored.

4.1. *ANP process for performance criteria evaluation*

The use of the ANP process requires the development of a decision network hierarchy. The network hierarchy determines the importance (and thus bounds) on the various performance criteria. It also allows these criteria to be linked to the 'strategic' direction of the organization. To keep the weighting model simple, we only investigate the effects of the following example performance criteria: Operating Costs, Average Work-in-Process (WIP), Average Flow-Time (FT), and Yield Rate (shown in figure 1). Each of these performance criteria is controlled by the objective

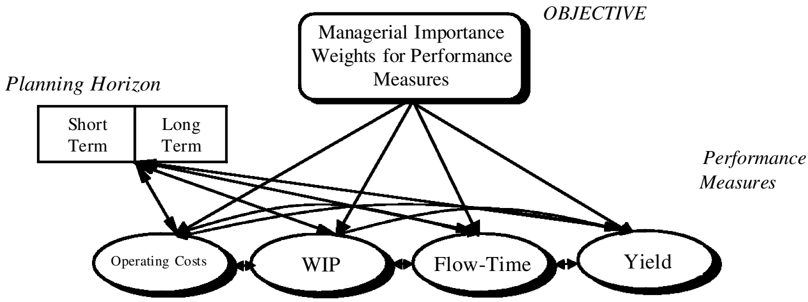

Figure 1. Network decision hierarchy for managerial weights elicitation using ANP.

of the ANP model, which is to garner managerial preference weights. The 'feedback' portions of the decision hierarchy include the strength of the relationships among the measures, represented by the arcs connecting the performance measures. The other feedback elements are the relationships of the measures with respect to short-term and long-term planning horizons. For example, the question for the first direction would be 'In the short-term, what is the relative importance of criterion 'x' when compared with criterion 'y'.' The opposite relationship would determine the relative importance of the measure from a short-term versus long-term perspective. This question may be worded, 'How much more important is criterion 'x' in the short-term versus the long-term.'

The above pairwise comparison questions are part of the first step in the ANP process. This step is similar to calculating relative preference weights among factors using the traditional Analytical Hierarchy Process (AHP). That is, a pairwise comparison matrix is developed where the relative importance of each of the factors, when evaluated with respect to the 'controlling' factor, is determined. Table 1 shows the pairwise comparison matrix for the performance measures when evaluating their relative importance weights with respect to the objective (the controlling factor).

4.2. *Determining relative importance weights*

Saaty (1980) recommends a scale of 1 to 9 (and 1 to 1/9) when completing pairwise comparisons among performance criteria or process factors. Once the pairwise comparisons are completed they form a pairwise comparison matrix (A). Then a local priority vector w (the vector of relative importance weights for the performance criteria, which is defined as the *e-vector* in the example figures) is computed as the unique solution to:

$$Aw = \lambda_{\max} w, \tag{7}$$

OBJ	Cost	WIP	FT	Yield	E-vector
Cost	1	3	2	4	0.462
WIP	0.333	1	0.5	2	0.156
Flow	0.5	2	1	4	0.294
Yield	0.25	0.5	0.25	1	0.088

Table 1. Pairwise comparison matrix and relative importance weight results for performance measures and impact on objective.

	OBJ	ST	LT	Cost	WIP	FT	Yield
Objective	0	0	0	0	0	0	0
Short Term	0	0	0	0.4	0.35	0.7	0.6
Long Term	0	0	0	0.6	0.65	0.3	0.4
Cost	**0.462**	0.109	0.371	0	0.25	0.25	0.4
WIP	**0.156**	0.109	0.41	0.35	0	0.35	0.4
FT	**0.294**	0.433	0.126	0.35	0.3	0	0.2
Yield	**0.088**	0.349	0.093	0.3	0.45	0.4	0

Table 2. Initial supermatrix for network hierarchy.

where λ_{max} is the largest eigenvalue of A. These calculations were completed using the AUTOMAN software for AHP analysis of advanced manufacturing technology (Weber 1993).

The results of this pairwise comparison matrix show that cost is viewed, by this decision-maker, to be the most important operational performance criterion (0.462), while yield is perceived as least important for the strategic goals of the organization. The relative importance weights of this matrix (*e-vector*) are then introduced into the supermatrix (table 2). The e-vector for the strategic clusters shows the relative importance of weights on the objectives of the organization (from table 1, with values equal to 0.462, 0.156, 0.294 and 0.088, respectively) as shown in bold in table 2. To complete the supermatrix, a total of 11 pairwise comparison matrices need to be completed. One for the performance measures–objective relationship, four for the performance measure interdependencies, and six for the interdependencies between the planning horizon and strategic clusters.

As we can see in the supermatrix in table 2, this decision-maker views FT and Yield to be relatively more important than Cost and WIP in the short-term planning horizon. The opposite seems to be true for the long-term planning horizon. In addition, a similar pattern exists in terms of where to put relative emphasis for each of the factors.

The next step in the ANP process is to determine the final set of relative importance weights for the performance measures from the supermatrix. This final set is determined by raising the supermatrix to a sufficiently large power (multiplying it by itself) such that the final weights remain stable (do not change with each additional multiplication, or converge). However, to ensure that convergence does occur, the supermatrix needs to be 'column stochastic'. One way of ensuring column stochasticity is to normalize the values in the columns so as to sum to 1. A column normalization is completed in this example by dividing each value in the column by the sum of the column values.

In this example the convergence to at least the fourth decimal place (10^{-4}) (the weights remained constant when they were rounded off to that fourth decimal place) occurred when the matrix was raised to the 32nd power. The results of the converged supermatrix are shown in table 3.

The weights from other managerial decision-makers need to be acquired in a similar fashion. In this illustration, we assume the maximum and minimum values for each factor from among all the decision-makers. These values are to be used as upper and lower bounds in the next phase of the methodology. The results of the bounds for the four performance measures are shown in table 4.

	OBJ	ST	LT	Cost	WIP	FT	Yield
Objective	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Short Term	0.171	0.171	0.171	0.171	0.171	0.171	0.171
Long Term	0.163	0.163	0.163	0.163	0.163	0.163	0.163
Cost	0.156	0.156	0.156	0.156	0.156	0.156	0.156
WIP	0.175	0.175	0.175	0.175	0.175	0.175	0.175
FT	0.165	0.165	0.165	0.165	0.165	0.165	0.165
Yield	0.171	0.171	0.171	0.171	0.171	0.171	0.171

Table 3. Converged supermatrix for network hierarchy.

Factor	Lower bound	Upper bound
Cost	0.156	0.220
WIP	0.096	0.187
FT	0.092	0.210
Yield	0.078	0.171

Table 4. Upper and lower bounds of relative importance weights for performance measures.

4.3. *System efficiency evaluation*

In this step, we evaluate the relative performance of the process over time using the RCCR/AR approach with the factor weight restrictions derived from the ANP technique.

We select a total of one input (Operating Cost) and three outputs (Average WIP, Average FT, and Yield). A characteristic of inputs is that smaller values indicate better performance, which is true with operating cost. For outputs, larger values represent better performance. While this is true with the Yield measure, Average WIP and Average FT need to be transformed to maintain the 'large is better' characteristic of outputs. Considering the reciprocal of these two measures performs this transformation.

The data utilized in the illustrative example are shown in table 5. These data are randomly generated from predefined uniform distributions using an Excel spreadsheet. We utilized the RANDBETWEEN function in Excel with distributions of (1 000 000, 2 000 000), (100 000, 150 000), (0.5, 2.0), and (0.900, 0.995) for Operating Costs, Average WIP, Average FT, and Yield, respectively. The data set was then mean normalized (with reciprocals of the Average FT and WIP taken) to eliminate any scale effects of the weight restrictions. In order to illustrate the effectiveness of our technique we have rearranged the sequence of some of the randomly generated data points to obtain an out-of-control pattern as demonstrated later.

The RCCR/AR model is then executed. The factor weight bounds for this decision environment are chosen from the ANP analysis described in the previous section. The results of this execution are shown in table 6.

4.4. *Process monitoring with individual control charts*

Initially, we generated the control limits for the *moving range chart*. The moving range values are calculated by using a two-period moving window. The results are summarized in table 6. The $\bar{R}$ value for this illustrative example is 0.155. The upper

Sample	Operating Costs ($)	Average WIP (units) (units)	Average flow-time (days)	Yield (%)
1	1364136	146853	1.57	0.982
2	1084794	123457	0.79	0.929
3	1972820	135029	0.81	0.903
4	1276697	126703	1.66	0.902
5	1656406	106452	1.00	0.968
6	1771203	126658	1.14	0.902
7	1196143	117088	1.59	0.924
8	1527999	130252	1.94	0.943
9	1684917	116697	1.84	0.956
10	1780074	144918	1.10	0.929
11	1315763	100807	1.75	0.973
12	1322362	134988	1.05	0.969
13	1124592	129700	1.03	0.968
14	1830507	145622	0.54	0.950
15	1624079	118980	1.52	0.907
16	1292410	109948	1.76	0.921
17	1965139	110104	1.77	0.914
18	1845709	139365	1.60	0.941
19	1924141	118859	1.86	0.945
20	1204509	121861	1.40	0.972
21	1693734	106682	1.47	0.969
22	1370221	139111	1.15	0.965
23	1149480	119458	1.28	0.959
24	1250170	109066	1.08	0.909
25	1128570	149699	0.67	0.966
26	1895706	100011	0.67	0.901
27	1937166	115911	1.20	0.995
28	1118864	119152	1.30	0.924
29	1570244	147984	1.32	0.956
30	1579692	107447	1.63	0.975

Table 5. Process data for illustrative example.

and lower control limits for the moving range chart are 0.51 and 0.00, respectively (a D_4 value of 3.268 is selected). Based on these limits, one can conclude that the variability of the process is in control since all the observations are within the limits. Since the *moving range chart* appeared to be in control, we then develop an *x-chart*.

The x-chart depicted in figure 2 is developed using 1, 2 and 3 sigma limits. The $\bar{x}$ value for the data set is 0.690. The upper and lower control limits for 1, 2 and 3 sigma standard errors are (0.83, 0.55), (0.97, 0.42) and (1.10, 0.28), respectively (the d_2 value utilized is 1.128). This chart is different from the traditional charts in that we consider the process to be out-of-control if a point falls below the lower 3-sigma limit. This approach is used because the index measured is a representation of the system efficiency and higher values indicate better performance. The periods in which the system performance index achieves a relatively high value can be utilized as possible benchmarks for process improvement.

It is evident from figure 2 that the process seems to be under control for this illustrative example. The process appears to have performed the best in periods 2 and 25 with scores of 1.055 and 1.042, respectively. These two periods can be utilized as possible benchmarks for improving the process performance in future time periods.

Sample	Relative efficiency	Moving range
1	0.652	—
2	1.055	0.403
3	0.746	0.309
4	0.708	0.038
5	0.664	0.044
6	0.548	0.116
7	0.796	0.248
8	0.582	0.214
9	0.562	0.020
10	0.529	0.033
11	0.781	0.252
12	0.748	0.033
13	0.897	0.149
14	0.726	0.171
15	0.582	0.144
16	0.526	0.056
17	0.489	0.037
18	0.482	0.007
19	0.484	0.002
20	0.809	0.325
21	0.605	0.204
22	0.699	0.094
23	0.865	0.166
24	0.840	0.025
25	1.042	0.202
26	0.669	0.373
27	0.534	0.135
28	0.875	0.341
29	0.576	0.299
30	0.638	0.062

Table 6. Process efficiency ratings.

Management must identify the policies and procedures utilized in these periods and seek to implement them.

In deriving the 1, 2 and 3 sigma zones, one can utilize stricter conditions to evaluate the system performance. It seems that the process has performed poorly in periods 15, 16, 17, 18 and 19 with scores of 0.582, 0.526, 0.489, 0.482 and 0.484, respectively. Under zone evaluation this does imply that the process is out-of-control because four out of five consecutive points fell beyond one standard error. Management should investigate this problem by utilizing separate charts for the four performance variables as shown in figures 3–6.

Initially, the *moving range charts* for the four variables Operating Cost, Average WIP, Average FT and Yield are investigated. Based on these charts, the variability of all four measures is observed to be in control. The x-charts are then generated for the four variables, which are shown in figures 3–6. In all cases, in general, the process seems to be in control with all points falling within 3-sigma limits.

In order to investigate further the case of system performance in periods 15, 16, 17, 18 and 19, where four out of five consecutive points fell beyond the 1-sigma limits, as indicated in figure 2, we developed the 1-sigma limits for the separate charts. The results of this analysis are interesting. Although, for the five periods in

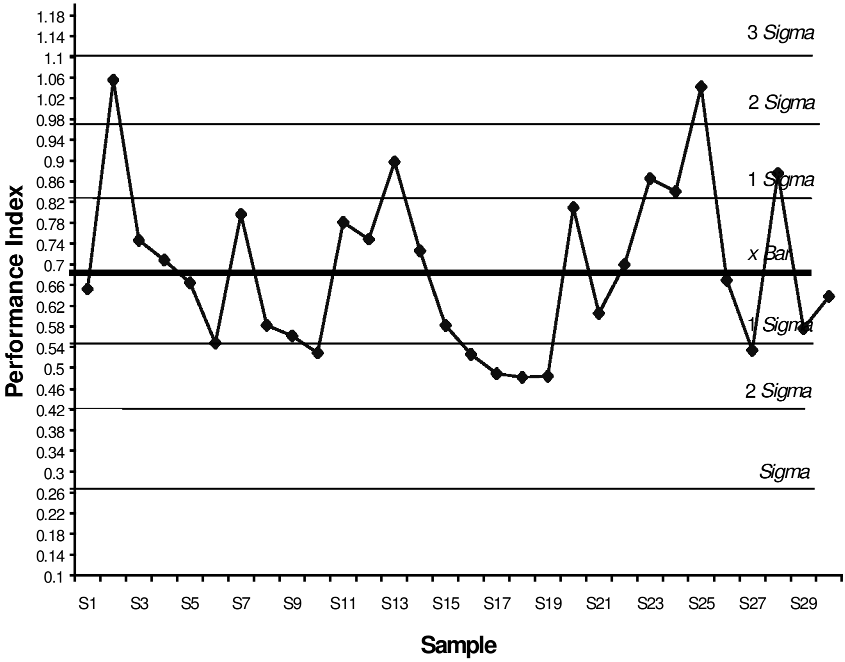

Figure 2. x-chart for system performance.

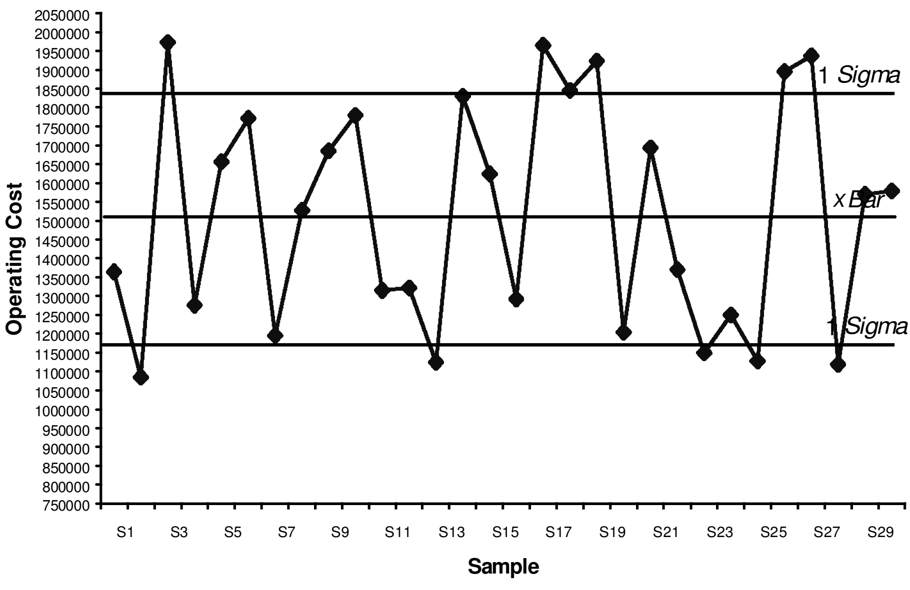

Figure 3. x-chart for operating costs.

question, we failed to see a specific out-of-control pattern in separate charts, the x-chart for Average FT came closest to being out-of-control. It is evident from this chart that for periods 15 to 19, three of five consecutive points fell beyond 1-sigma limits. In addition, note that period 18 had an Average FT value of 1.6, which is very close to the 1-sigma upper limit of 1.63. Since smaller values of Average FT indicate

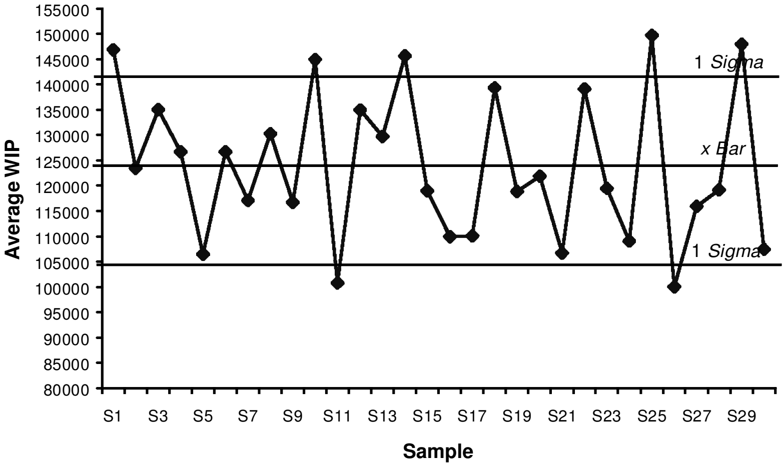

Figure 4. x-chart for Average WIP.

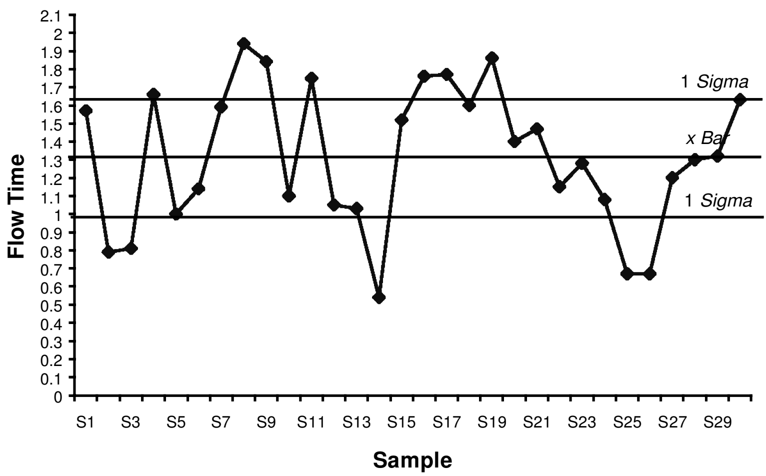

Figure 5. x-chart for Average FT.

better performance, it can be concluded that the process was not very efficient during these time periods. This result, coupled with the fact that relatively low yield rates and high operating costs occurred during these time periods, made the integrated system performance index be out-of-control. This result highlights the fact that while separate charts are marginally in control the overall process can be out-of-control. Management needs to investigate the causes for relatively high Average FT, low Yield Rates, and high Operating Costs for these periods in question.

It is also possible for the system efficiency to be in control and for some individual factors to be out-of-control. This could happen if the decision-maker places less emphasis (weight) on a particular factor(s), which happens to be out-of-control in the individual chart, but this does not affect the efficiency score much because of its relatively lesser weight in the DEA model.

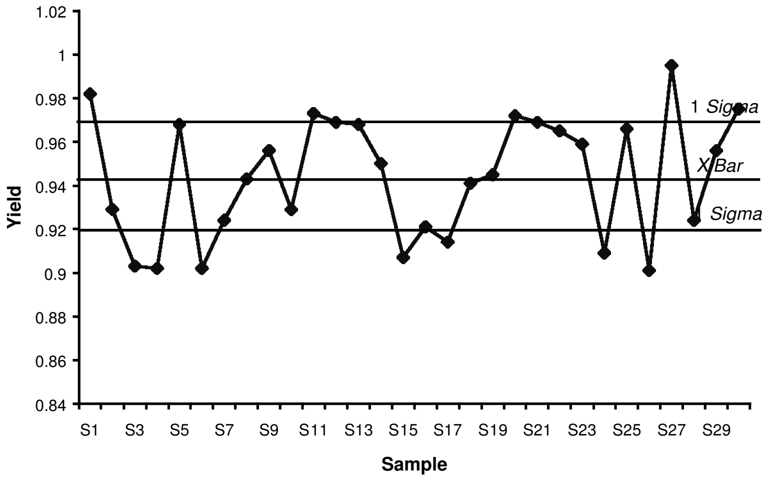

Figure 6. x-chart for yield.

All the patterns in control charts—such as the point outside the control limits, a sudden shift in the process performance average, cycles, trends, instability—can be detected using this method. Once the particular pattern is observed then a more detailed analysis using separate charts can be used for each of the performance measures under investigation.

From an ongoing evaluation standpoint, we suggest dropping the period (DMU) with the lowest efficiency score as a new period enters into the model. This ensures that each new period is evaluated or challenged against the best of the pervious periods. This would in fact mean that the UCL and LCL limits of the individual control chart would be evaluated on better performing benchmarks from period to period, which is consistent with the concept of continuous process improvement. While the AR values that represent the relative importance of various factors remain the same, the RCCR values have to be recalculated with the new DMU. However, the recalculations would not be very cumbersome since the approach can easily be automated using computer software.

5. Conclusions and extensions

In this paper, we propose a methodology for developing a control chart for manufacturing system monitoring. We have utilized a combination of ANP, a DEA model with added ranking ability, and individual charts for performance evaluation and process monitoring. We have demonstrated our methodology through a numerical example.

In summary, the primary advantages of this method are: (1) it effectively monitors the system performance in the presence of multiple measures, and does so by tracking a single integrated index; (2) it effectively integrates decision-makers' preferences into the process; (3) it overcomes some of the limiting assumptions of traditional methods such as multivariate normality and independence.

Although we did address some preliminary ways of using this as a benchmarking tool, more work is required in this area as to the identification of appropriate benchmark periods for process improvement. In addition, the sensitivity analysis of this process needs to be investigated to determine the parameter shifts associated with the selection of decision factors, decision-makers' perceptual and managerial variabilities, and alternative approaches for evaluating ranges and control limits. Integration of qualitative performance measures can also be investigated. This is possible since there are a number of techniques that can be used to quantify qualitative measures and integrate them into a DEA-type analysis. Its utility with respect to actual managerial understanding and eventual acceptance also needs to be investigated further.

References

ADAMS, S., SARKIS, J. and LILES, D., 1995, The development of strategic performance metrics. *Engineering Management Journal*, **7**(1), 24–32.

ALT, F. F., 1984, Multivariate quality control. In S. Kotz, N. L. Johnson and C. R. Read (eds) *The Encyclopedia of Statistical Sciences* (New York: Wiley), pp. 110–122.

ANDERSEN, P. and PETERSEN, N. C., 1993, A procedure for ranking efficient units in data envelopment analysis. *Management Science*, **39**(10), 1261–1264.

AZHAR, T. M. and LEUNG, L. C., 1993, A multi-attribute life cycle approach to replacement decisions: an application of Saaty's system with feedback method. *The Engineering Economist*, **38**(4), 321–342.

BITITCI, U. S., SUWIGNJO, P. and CARRIE, A. S., 2001, Strategy management through quantitative performance measurement systems. *International Journal of Production Economics*, **69**, 15–22.

CHARNES, A., COOPER, W. W. and RHODES, E., 1978, Measuring the efficiency of decision making units. *European Journal of Operational Research*, **2**(6), 429–444.

EVANS, J. R. and LINDSAY, W. M., 1999, *The Management and Control of Quality* (Cincinnati, Ohio: South-Western College Publishing).

GHALAYINI, A. M., NOBLE, J. S. and CROWE, T. J., 1997, An integrated dynamic performance measurement system for improving manufacturing competitiveness. *International Journal of Production Economics*, **48**(3), 207–225.

HAMALAINEN, R. P. and SEPPALAINEN, T. O., 1986, The analytic network process in energy policy planning. *Socio-economic Planning Sciences*, **20**(6), 399–405.

HAWKINS, D. M., 1991, Multivariate quality control based on regression adjusted variables. *Technometrics*, **33**, 61–75.

JACKSON, J. E., 1985, Multivariate quality control. *Communications in Statistics – Theory and Methods*, **14**, 2657–2688.

KAPLAN, R. and NORTON, D., 1996, *The Balanced Scorecard: Translating Strategy into Action* (Boston, MA: Harvard Business School Press).

KUENG, P., 2000, Process performance measurement system: a tool to support process-based organizations. *Total Quality Management*, **11**(1), 67–85.

LOCKAMY, A. and COX, J. F., 1994, *Reengineering Performance Measurement* (Burr Ridge, IL: Irwin Professional Publishing).

LOWRY, C. A. and MONTGOMERY, D. C., 1995, A review of multivariate control charts. *IIE Transactions*, **27**, 800–810.

MEADE, L., SARKIS, J. and LILES, D. H., 1997, Justifying strategic alliances: A prerequisite for virtual enterprising. *OMEGA*, **25**(1), 29–42.

NANNI, A. J., DIXON, J. R. and VOLLMANN, T. E., 1992, Integrated performance measurement- management accounting to support the new manufacturing realities. *Journal of Management Accounting Research*, **7**, 1–19.

NEELY, A., GREGORY. M. and PLATTS, K., 1995, Performance measurement system design: a literature review and research agenda. *International Journal of Operations and Production Management*, **15**(1), 80–116.

SAATY, T. L., 1980, *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation* (New York: McGraw Hill).

SAATY, T. L., 1996, *Decision Making with Dependence and Feedback: The Analytic Network Process* (Pittsburgh, PA: RWS Publications).

SAATY, T. L. and TAKIZAWA, M., 1986, Dependence and independence: from linear hierarchies to nonlinear networks. *European Journal of Operational Research*, **26**, 229–237.

Sabri, E. H. and Beamon, B. M., 2000, A multi-objective approach to simultaneous strategic and operational planning in supply chain design. *Omega*, **28**(5), 581–598.

Sarkis, J., 1998, Evaluating environmentally conscious business practices. *European Journal of Operational Research*, **107**(1), 159–174.

Sarkis, J. and Talluri, S., 1996, Efficiency valuation and business process improvement through internal benchmarking. *Engineering Valuation and Cost Analysis*, **1**(1), 43–54.

Suwignjo, P., Bititci, U. S. and Carrie, A. S., 2000, Quantitative models for performance measurement system. *International Journal of Production Economics*, **64**, 231–241.

Thompson, R. G., Langemeier, L. N., Lee, C. T. and Thrall, R. M., 1990, The role of multiplier bounds in efficiency analysis with application to Kansas farming. *Journal of Econometrics*, **46**, 93–108.

Weber, S. F., 1993, A modified analytic hierarchy process for automated manufacturing decisions. *Interfaces*, **23**(4), 75–84.

Wierda, S. J., 1994, Multivariate statistical process control – recent results and directions for future research. *Statistica Neerlandica*, **48**, 147–169.

Woodall, W. H. and Ncube, M. M., 1985, Multivariate CUSUM quality control procedures. *Technometrics*, **27**, 285–292.