ASSESSMENT OF MANUFACTURING PERFORMANCE USING DATA ENVELOPMENT ANALYSIS

by

ANGELA BENBARKA

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ABSTRACT

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Angela BenBarka, M.S.

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Supervising Professor: Revenor C. Baker

In today's global and highly competitive economy, organizations are constantly monitoring their performance and the performance of their competitors. With technological advancements and increased expectations from consumers, time becomes a critical factor in an organizations' ability to sustain their advantage over competitors. By understanding the multiple components which compose their performance and quickly identifying and addressing inefficiencies within the systems, an organization can maintain and possibly increase their share of the marketplace.

This research will assess the feasibility of data envelopment analysis (DEA) as a tool for organizations to measure their performance over time. DEA has been widely used and accepted as methodology for performance evaluations and benchmarking. The

basic concept of directing methodology at frontiers rather than central tendencies such as statistical regression, gives DEA an advantage over previous, traditional methods. DEA is capable of identifying relationships among entities that traditional methods are not able to identify. It quantifies relations of entities in a direct manner without requiring several assumptions or variations on data sets.

DEA will be applied to a manufacturing facility for assessment of the facility's monthly performance and distinction of good performing months from poor performing months. The manufacturing facility is one of many manufacturing facilities of a large publicly-owned corporation. The facility has a large product mix with over 100 different formulations, resulting in multiple inputs to multiple outputs. Faced with the large product mix, executives from the manufacturing facility are constantly challenged to meet productivity levels and maintain an edge on their competitors all the while fulfilling customer expectations, meeting industry regulations, and staying abreast technological advancements.

This research will provide a mechanism for manufacturing executives to easily and rapidly distinguish facility performance. Concepts of DEA will be extended to consider modeling of DEA efficiency scores to evaluate performance over time and determine the overall efficiency or health of the facility. The DEA model will then be utilized as input into classical statistical control charts to track performance over time. Monthly production reports associated with the extreme values on the control charts will be evaluated by experts within the manufacturing facility for validation of the DEA model.

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CHAPTER 1

INTRODUCTION

Technological advancements and increased consumer purchasing power has created a tremendous growth in the global economy. Over the last few decades there has been an explosion of products and services available to the average consumer. What was once identified as a product or service for the elite or wealthy is now attainable for the average household. Advancements such as self-serve or automated systems, 24-hour access, and internet applications have proven beneficial for both consumers and corporations. However, these advancements have also provided a competitive foundation for new businesses. Corporations may no longer rely on their brand name or unique product characteristics to maintain their market share.

The transition to a larger consumer mix coupled with the ever increasing and volatile customer demand of products and services has placed extreme pressures on manufacturers. Often customer demands require companies to continuously meet low product cost, short delivery time, high product quality, and high product variety. This is not an easy task. It requires the manufacturer to have a flexible production schedule, adequate inventory of materials, robust manufacturing processes, and adaptable equipment that supports multiple product mixes with interchangeable parts. Basically, an organization must have a strong knowledge of their manufacturing systems.

Manufacturing systems have always existed. Dating back to ancient times, manufacturing methods were applied to construct pyramids, roads, and cottages. Of course these methods were quite different from those applied today, but nevertheless systems were implored to produce a product. Manufacturing systems became more widespread in the 1700 and 1800's with the industrial revolution. Machines began replacing human craftsmanship and large factories replaced the small apprentice shops. The rail system, urban settlement, and the influx of industrial operations evolved during the twentieth century and defined manufacturing systems with mass production, specialization of labor, mechanized assembly lines, and standardized product designs. History has shown that technological advancements have changed how organizations conduct business and even how some industries become extinct. Therefore, it becomes critical for organizations to know their manufacturing systems thoroughly and understand how the systems impact business strategies.

Gaither [1996] identifies three main components of business: production, marketing, and finance. Each component has a distinct role and unique function it provides to the business. Quite often each component focuses separately to achieve their goals rather than functioning together to achieve not only their goals but goals of the business strategy. Data envelopment analysis (DEA) is a resourceful tool for such a task. DEA can take multiple inputs and outputs of the entity or operating unit under evaluation and reduce the analysis to a single quantity for easier decision making.

This research will utilize DEA to develop a mathematical model to assess the performance of a manufacturing facility over time. The goal is to determine the ability

of DEA to utilize comparative metrics over time to distinguish performance levels. DEA has been used and accepted as a performance measurement tool and benchmarking tool. Few evaluations have included the use of DEA with comparative metrics over time.

This thesis is structured in the following format: Chapter 2 gives an overview of manufacturing systems. It describes initial developments and techniques for manufacturing systems and gives a historical review of the development of data envelopment analysis. This chapter defines DEA and depicts its applications within the business community.

Chapter 3 describes the methodology and considerations given to the mathematical model developed. It describes the type of data, data variables, and model development. Pertinent background information of the manufacturing facility under evaluation is noted to provide historical reference for methods applied.

Chapter 4 describes the results and analysis of the DEA model developed. It gives the results obtained from the historical production data set and provides analysis of the model against the current production data set. Expert analysis by members of the manufacturing facility will provide feasibility of the DEA model.

CHAPTER 2

OVERVIEW OF MANUFACTURING SYSTEMS

This chapter gives an overview of manufacturing systems. It describes initial developments and techniques for manufacturing systems and gives a historical review of the development of data envelopment analysis. This chapter defines DEA and depicts its applications in the business community.

2.1 Development of Manufacturing Operations

Manufacturing systems were first evaluated and analyzed in the late 1800's by Fredrick Winslow Taylor. Taylor studied the manufacturing processes and operations of his time, and applied scientific principles to address industry problems. He worked his way as a general laborer to a chief engineer. Advancements in his career are credited to his investigative nature and intolerance for waste. While working in industry, Taylor developed a systematic approach to improve worker efficiencies through instruction cards, materials specifications, standardized work methods, and work flow. Taylor eventually left industry to form a consulting firm where his system could be used on a larger range of applications. For all his contributions, Taylor is known as the "father of scientific management".

Others followed Taylor with contributions to scientific management. Frank Gilbreath evaluated motion studies and methods, while Lillian Gilbreath conducted fatigue studies and looked at human factors at work and employee selection and

training. Henry Gantt developed the Gantt chart and took a humanistic approach to labor with incentive pay programs. Carl Barth consulted with the automobile industry applying mathematical analysis using the slide rule. Harrington Emerson worked with efficiency techniques in the rail industry, while applications to education and government sectors were provided by Morris Cooke. Each individual has contributed valuable applications and approaches that further enhanced scientific management and production techniques used today.

2.2 Mathematical Modeling of Processes

Taylor initiated the foundation for management science or operations research as it is often referred to today. Operations research has grown and become a prevalent component of business. Gaither [1996] states "operations research, like scientific management, seeks to replace intuitive decision making for large complex problems with an approach that identifies the optimal or best, alternative through analysis". Operations research takes a quantitative approach to decision making. It makes use of mathematical models to define and depict processes for further review, evaluation, and decision making.

Anderson et al [1994] identifies George Dantzig's simplex method for solving linear programming problems as a significant development in mathematical modeling. From Dantzig's work, other methodologies followed, including publication of the first operational research book presented by Churchman, Ackoff, and Arnoff. Also during this time, M.J. Farrell wrote an article that has been credited by Cooper et al [2004] and Coelli et al [2005] as the beginning of data envelopment analysis (DEA). Mathematical

models developed by Boles (1960), Shephard (1970) and Afriat (1972) suggested applications of DEA, but the methodology did not gain interest until introduced by Charnes, Cooper, and Rhodes (1978).

2.3 Data Envelopment Analysis (DEA)

The mathematical programming model known as DEA is an application of linear programming. It has been used to measure the efficiency of decision making units with similar if not the same performance objectives. For example, DEA has been used to determine the most efficient store from a chain of stores or the best hospital from all hospitals within a particular region. The performance of each unit is determined relative to the performance of all units within the system or area.

DEA uses a linear programming model to construct a hypothetical frontier or surface area over the data. Efficiency measures are then calculated relative to this frontier or area. Coelli et al [2005] Cooper et al [2006] gives credence to the name data envelopment analysis, because such a frontier "envelops" the data points.

Charnes, Cooper, and Rhodes (1978) initially described data envelopment analysis (DEA) as a 'mathematical programming model applied to observational data that provides a new way of obtaining empirical estimates of relations – such as production functions and/or efficient production possibility surfaces – that are cornerstones of economics'. Since its inception, DEA has been applied to a variety of entities with diverse contexts in several different countries. DEA has been used to study the performance of government programs, hospitals, schools/universities, corporations, and even performance of countries or sectional regions. Due to its ability

to consider multiple inputs and multiple outputs without strict adherence to statistical assumptions, DEA has provided a flexible scheme for researchers to adapt. Cooper, Seiford, Tone (2000) have adapted the methodology for modeling operational processes for performance evaluations. Further research by Zhu (2002) has provided a number of DEA spreadsheet models that can be applied to performance evaluations and benchmarking.

The basic concept of directing methodology at frontiers rather than central tendencies such as statistical regression, gives DEA an advantage over previous, traditional methods. DEA is capable of identifying relationships among entities that traditional methods are not able to identify. DEA quantifies relations of entities in a direct manner without requiring several assumptions or variations on the data set. For these reasons, it continues to be a widely accepted and studied technique with many real world applications.

The objective of this research is to develop a mathematical model through data envelopment analysis to assess monthly performance of a manufacturing facility and utilize the model to determine highly productive months from the average or poor performing months. While DEA has been widely used and accepted as methodology for performance evaluations and benchmarking, little research has been conducted for the use of DEA with comparative metrics over time. This research will assess the feasibility of data envelopment analysis as a tool for organizations to measure performance over time.

CHAPTER 3

METHODOLOGY

This chapter describes the methodology and considerations given to the mathematical model developed. It describes the type of data, data variables, and model development. Pertinent background information of the manufacturing facility under evaluation is noted to provide historical reference for methods applied.

3.1 Basis of DEA

DEA is considered to be non-parametric. Its application does not require units to adhere to strict assumptions or follow typical statistical rules. As Cooper et al [2006] and others have stated, DEA allows the use of an entities' own requirements or needs to determine efficiencies as well as inefficiencies. Predetermined or fixed values are not imposed upon the data for analysis, and the application is capable of processing multiple data variables. For these reasons, DEA is seen as a robust measurement tool and will be utilized in this research for assessment of monthly performance.

According to Coelli et al [2005], performance is a relative concept. Performance of a facility can be measured in relation to one year relative to another year or even in relation to another facility. It can be portrayed as one measurement for the facility or delineated as one measurement for each department of the facility. Therefore, performance as measured by the production manager may differ from performance measured by the quality assurance manager or even by the accountant.

Performance is a quantitative measurement, however, the components that comprise this measurement are subjective and at the discretion of the manager.

3.2 Data Variable Selection

The multiple components that comprise performance and their subjective nature were considered when determining data variables for the manufacturing facility under review. Recall, the objective of this research is to develop a mathematical model through DEA to assess monthly performance of a manufacturing facility and utilize the model to determine the highly productive months from the average or poor performing months. Therefore, the data variables should portray overall performance of the manufacturing facility and should include those components or inputs and outputs that are required by the facility for operation.

The manufacturing facility under review is one of many manufacturing facilities of a large publicly-owned corporation. The facility has a large product mix with over 100 different formulations and distributes the products world wide. The facility manufactures in a highly regulated industry, meeting U.S. government requirements as well as government requirements imposed by their international customers. Faced with the large product mix and multi-jurisdictional requirements, managers from the manufacturing facility review productivity levels and evaluate performance of the facility on a monthly basis. It is from these monthly managerial reports that data variables were selected.

The monthly managerial reports contain performance metrics for all departments in the manufacturing facility, including metrics for cost accounting. Each

report contains over 100 charts, graphs, and data tables with over 50 performance metrics represented. To prevent any negative effects to the model, all performance metrics were not considered. Metrics which depicted production operations and those that depicted the restrictions imposed by industry regulations were chosen for the model. It should be noted that industry regulations are typically those metrics embedded as quality parameters. The regulations for this industry mandate a separate function for production and the quality control units.

Initially, 14 data variables (6 output and 8 input variables) were considered for the model. However, upon further review of the data, some variables were seen to be correlated so of the original 14 data variables only 9 variables (4 output and 5 input) were selected for use in the model. Output variables include: # of batches, actual units, % of production standard, and % on-time release. Input variables include: # of shifts, # of reworks, # of exceptions, % packaged units resampled, and % of material lots exception-free. Data from January 2003 through December 2005 was collected for these variables for model development and will be referred to as the 'historical production data set'. Similarly, data from January 2006 through December 2006 was collected for verification of the model and will be referred to as the 'current production data set'. Raw data for the variables selected for the 'historical production data set' and the 'current production data set' are presented in Appendix A as Tables A.1 and A.2, respectively.

3.3 DEA Model Development

The original DEA model was formulated by Charnes, Cooper, and Rhodes, presented in the article "Measuring the efficiency of decision making units" in the *European Journal of Operational Research, 2, (1978).* The model had an input orientation and assumed constant returns to scale. Extending from the original model, Fare, Grosskopf, and Logan (1983) and Banker, Charnes, and Cooper (1984) proposed models with variable returns to scale. Others followed with additive and multiplicative models, costing, allocation, bounded-variable, and super-efficiency models. This is by no means an exhaustive listing of DEA models, but an illustration of developments that have been pursued since inception of the original model. The models use non-linear fractional programming models that are converted into linear programming problems by forcing the denominator of outputs to input ratio to equal one.

The model for this thesis will utilize the performance measurements from monthly production reports as the output and input variables to determine the overall performance or efficiency of the month. Each month is treated as a decision making unit under evaluation and as such a performance or efficiency score will be established for each month. The model is represented mathematically by the following:

$$\text{MAX} \quad \sum_{r=1}^{s} u_r y_{r0} \Big/ \sum_{i=1}^{m} v_i x_{i0}$$

$$\text{subject to:} \quad \sum_{r=1}^{s} u_r y_{rj} \Big/ \sum_{i=1}^{m} v_i x_{ij} \leq 1 \text{ , } j = 1,...n$$

$$u_r, v_i \geq 0; \; r = 1,...,s; \quad i = 1,...,m.$$

Here the y_{rj}, x_{ij} are the positive, outputs and inputs of the jth month or decision making unit (DMU) and the u_r, $v_i \geq 0$ are the weights that become the solution of the problem. The weights are based on the data set. Each DMU is assigned the best set of weights with the values varying from one DMU to another. Of course the expectation is that the weights would allow the DMU to obtain the best possible efficiency score of 1.

Other models were considered for use. However, these models placed limits on the inputs and/or outputs, or focused on identifying the inefficiencies within the DMUs. Since the data is input oriented, based on sales forecast and sales demand, and contains inherent restrictions due to the tight regulations of the industry, the original model developed by Charnes, Cooper, and Rhodes was found to be the most appropriate model. This model provided pertinent information for use in projecting aggregate weights for the performance input and output metrics.

DEA Solver software, developed by Tone [2006], combined with Excel spreadsheet capabilities were used for calculations of the model. Initially, the model was used on the historical production data set to obtain weights for each input and output variable and give an overall efficiency score for each month or DMU. These efficiency scores and the respective weights for each variable are presented in Appendix A as Tables A.3 and A.4.

The individual weights assigned to each DMU were then averaged to obtain a single weight value or aggregate weight for each variable. The aggregate weights for each variable are presented in Appendix A as Table A.5. The model was re-iterated a 2nd time using the aggregate weight values to obtain efficiency scores for each DMU of

the historical production data set. The model was then applied to the current production data set. The efficiency scores obtained with the aggregate weights for the historical production data set and the current production data set are presented in Appendix A as Tables A.6 and A.7, respectively.

The primary objective of this research is to evaluate DEA as a possible tool for organizations to use for measuring performance over time. The model was developed with a historical production data set including performance data from the previous thirty six months, and the model was confirmed with the most recent twelve months of performance data or current production data set. The basic concept was to utilize the historical data set which contained the natural variations of the manufacturing facility over time for development and utilize the current data set which contains the state of the facility today for verification of the model. Assessment of both data sets against the model follows in the next chapter. The ability of the model to distinguish good performing months from average or poor performing months is seen through analysis of the model.

CHAPTER 4

RESULTS AND ANALYSIS

This chapter provides the results and analysis of the DEA model developed. It gives the results obtained from the historical production data set and provides analysis against the current production data set. Expert analysis by members of the manufacturing facility will provide feasibility of the DEA model.

4.1 Historical Production Data Set

As Charnes, Cooper, and Rhodes (1978) first proposed, the efficiency measure of an entity or DMU is obtained as the maximum ratio of weighted outputs to weighted inputs where the similar ratios for each entity is less than or equal to one. This was applied for the first iteration of the model. The performance of each month was measured as the maximum ratio of the weighted outputs to weighted inputs and no month obtained a performance measurement greater than one. The number of outputs and inputs was not restricted and all were positive values. From the first iteration, the performance measurements or efficiency scores obtained were extremely favorable. Of the 36 months, 17 months had a performance measurement of one with the lowest measurement equaling 0.918 for February 2003. Refer to Table A.3 in Appendix A. A performance score of one is considered to be the best or a good performing month.

Performance scores obtained from the 2nd iteration of the model may appear to be unfavorable at first glance. Of the 36 months, no months had a performance

measurement of one. The highest performance score was 0.338 obtained by January 2005 and the lowest 0.228 obtained by December 2005. Refer to Table A.6 in Appendix A. However, the performance scores of the 2nd iteration were calculated using the aggregate weights versus the individual weights used in the 1st iteration. The individual weights were assigned the best weight value for each variable based on the data for that month. The aggregate weights are based on the average weight for each variable based on the data for all months in the historical production set. Taking a closer look at individual weight values listed in Table A.4 in Appendix A, it is easily seen that some variables are assigned a weight of zero. For example, actual units and % of production standard variables were assigned a value of zero for the months February 2003 through July 2003. Realistically, how can the performance of a month be determined without consideration to the actual number of units and the production standard. The 1st iteration of the model was primarily concerned with establishing the best performance score for each month based on the weights assigned to the variables for that month.

The objective of this research is to obtain a set of weights for the variables that would depict performance scores as seen over time. Examining the aggregate weights listed in Table A.5 in Appendix A, the values are all greater than zero and appear to be realistic values. Therefore, the performance scores obtained with the aggregate weights may not provide the most efficient or best performance score, but may distinguish the performance levels over time.

The performance scores from the 2nd iteration of the model using the aggregate weights were evaluated using analysis of variance to determine if there is a significant difference between the monthly performance metrics. Results of the analysis of variance are presented in Appendix A as Table A.8. The ANOVA Table A.8 decomposes the variability of the performance scores into two contributions, namely variability due to the month and variability due to the year. The analysis was performed with a type III sum of squares meaning the contribution of the month is measured without the influence of the year. Similarly, the contribution of the year is measured without the influence of the month. The results indicated that both the monthly performance metrics and performance metrics for the year are statistically significant. Therefore, at least one monthly performance metric as well as one year is different from others.

Considering this, multiple range tests were conducted to determine where the differences occurred. Results for the multiple range tests conducted for the performance metric by month is presented in Appendix A as Table A.9. Table A.9 identifies five homogenous groups, where within a group, the mean monthly performance metrics show to be statistically the same or no differences. From Table A.9, December is the one month where the monthly performance metrics show to be statistically different from all other months. Results for the multiple range tests conducted for the performance metric by year is presented in Appendix A as Table A.10. Table A.10 identifies two homogenous groups. Therefore, since three years were evaluated for the 2nd iteration, one year is statistically different from the other two years,

namely the first year. This seems logical. One would expect performance scores to improve with time.

The performance scores were also evaluated using control charts. Individual mean and moving range charts were constructed for the historical production data set. Charts are presented in Appendix B as Figures B.1 and B.2, respectively. The individuals chart showed a fairly stable process for the performance scores with an upper control limit of 0.365 and a lower control limit of 0.227. The moving range chart depicted more of the differences in the performance scores. The average range of the performance scores for the historical production data set was 0.026. Two months, January 2004 and December 2005, exceeded the moving range control limit. The data was reviewed with experts from the manufacturing facility to determine if a particular event or change occurred at this time that could have attributed to the high variability. No assignable causes could be identified for these months. Therefore, all performance scores of the historical production data set were maintained for establishment of control limits for the model and applied to the current production data set.

4.2 Current Production Data Set

As with the historical production data set, a 3rd iteration of the model using the aggregate weights was applied to the current production data set. The performance scores for the current production data set are presented in Appendix A as Table A.7. The performance scores generated with the current production data set are comparable to the scores generated with the historical production data set. The average performance score for the current production data set is 0.31 with overall variability of

0.02, whereas the average performance score for the historical production data set is 0.30 with an overall variability of 0.03.

The performance scores for the current data set were plotted on Individuals and moving range charts using the control limits established by the historical production data set. Individual and moving range control charts are presented in Appendix B as Figures B.3 and B.4, respectively. Just as with the performance scores for the historical production data set, the individual performance scores appear to be fairly stable while the moving range depicts more of the variability from month to month. A side by side comparison of both production data sets is portrayed in Appendix B as Figures B.5 and B.6. From the figures, January and July 2004, January and August 2005, and January and July 2006 appear to be the best performing months. The lowest or poor performing months appear to be December 2003, December 2005, June 2006, and December 2006. Overall, the model has identified January as a high performing month and December as a poor performing month. As such, these months were considered for evaluation by experts within the manufacturing facility.

4.3 Validation of the DEA Model through Expert Analysis

Individuals from the manufacturing facility were called upon to assess the model's ability to assess good performing and poor performing months. The individuals are referred to as "experts" and possess considerable knowledge about the facility operations and manufacturing systems. An expert from the Quality Assurance department and an expert from the Production department participated in the validation exercise.

The experts were given complete monthly production reports for July 2004 and December 2003 for assessment. All dates were obliterated from the reports given to the experts to ensure an unbiased assessment. The experts were instructed to review the monthly reports and in their opinion determine if the performance data represented in the report would be considered a "good" performance month or a "bad" performance month.

Analysis of production reports by the experts did not validate the DEA model. The Quality Assurance expert indicated that December 2003 was a good performing month and July 2004 was a poor performing month. The Production expert indicated that both months were good performing months. Recall from previous discussion, the model had identified December 2003 as a poor performing month and July 2004 as a good performing month.

It is not too surprising that the DEA model was not validated by the expert analysis. A complete monthly production report contains well over 100 pages of tables, charts, and graphs describing performance data of the facility for a given month. To expect an individual to process this amount of quantitative data and reach a single conclusion is an enormous task. When reviewing the analysis, each expert expressed their challenge in doing just this. Both experts described a quantitative method that was used to reach their decision of a good month or poor month. Each attempted to be unbiased considering multiple parameters and factors, but when faced with determining a single indicator for the month, both experts based their final decision on the data within their respective areas. Once the month of the production report under review by

the experts was revealed, each expert identified with the model's assessment. The experts remarked that December is a light month for production capacity, since the facility ceases operations for approximately two weeks in December. Additionally, July and August are typically heavy months for production, in order to compensate for facility downtime in June and facility holidays.

4.4 Conclusion

The DEA model developed was not validated by expert analysis. However, the model, in conjunction with classical statistical control charts, did identify a difference in performance levels among the months. The difference identified by the model was also acknowledged by experts from the manufacturing facility. Therefore, credence should be given for the use of DEA with comparative metrics over time.

Recall, the objective of this research was to develop a mathematical model through DEA to assess monthly performance of a manufacturing facility and utilize the model to determine highly productive months from the average or poor performing months. The objective was fulfilled through the research conducted. The model distinguished a high performing month from a lower performing month.

While the model did not depict extreme performance levels, this could be a factor of the actual performance data. Afterall, the manufacturing facility assessed, is part of a large, publicly-owned corporation and the performance of the facility is fairly stable. One would not expect to see extreme performance levels.

Another factor to consider is limitations on the data. The performance data did not contain cost or equipment operation data. Both comparative metrics were not

consistently reported in the production reports for the time periods, and as such were not available for model development. Inclusion of cost and equipment metrics may have resulted in sharper detection of performance levels by the model, however it was not possible for this research.

Irregardless of the model developed, experts from the manufacturing facility expressed interest in DEA and its uses for measuring performance over time. Currently, the facility spends a considerable amount of time and resources preparing graphs, charts, and data tables for the monthly production report, not to mention the amount of time spent for review and discussion of the report. To take the complex, multi objective task of performance measurement and reduce it to a single evaluation would be a powerful tool for the organization. Facility efforts could be focused on managing technology changes and regulatory requirements to provide manufacturing system improvements and compliance. Therefore, resources would be allocated for system suitability as well as enhancements.

In summary, the concepts of DEA were extended to include modeling of efficiency scores to assess performance over time and determine the overall efficiency or health of the organization. The DEA model was utilized as inputs into classical statistical control charts to track facility performance over time. Monthly production reports representing extreme values on the control charts were evaluated by the facility experts for validation of the model. While the expert analysis did not validate the DEA model, the model was found useful and indicative of facility performance. Therefore,

the use of DEA for evaluating comparative metrics over time is feasible. DEA should be considered by organizations as a quantitative tool to measure performance over time.

APPENDIX A

TABLES

TABLE A.1

RAW DATA FOR THE HISTORICAL PRODUCTION DATA SET

DMU	Batches (#)	Actual units (mm)	Standard (%)	On-time release	Shifts (#)	Reworks (#)	Exceptions (#)	Units resampled (%)	Material exception free (%)
Jan '03	75	5.9	81	0.95	143	2	10	0.86	98.5
Feb '03	64	6.0	88	0.90	134	4	15	2.46	98.4
Mar '03	61	6.9	82	0.91	166	2	9	1.10	98.3
Apr '03	69	6.6	83	0.95	179	4	22	2.75	99.5
May '03	83	8.2	77	0.91	180	8	14	2.75	98.2
June '03	53	5.3	90	0.96	128	6	8	1.56	99.5
July '03	66	7.1	92	0.99	165	5	8	3.33	98.8
Aug '03	72	8.0	98	0.91	169	5	13	2.38	98.6
Sept '03	71	7.1	86	0.98	145	4	11	3.43	98.3
Oct '03	73	7.4	96	0.99	158	2	16	3.00	98.8
Nov '03	67	6.2	91	0.97	160	3	13	2.12	98.4
Dec '03	36	3.9	91	0.97	97	1	16	1.04	99.1
Jan '04	76	7.2	100	0.98	137	0	2	1.35	98.8
Feb '04	66	7.5	99	0.98	138	5	12	1.84	98.7
Mar '04	73	8.3	99	0.99	155	0	13	0.88	99.1
Apr '04	77	8.2	103	0.98	154	5	7	2.59	99.1
May '04	68	7.6	98	0.95	141	3	17	2.15	98.8
June '04	57	6.1	96	0.99	122	4	15	1.47	98.7
July '04	83	6.6	90	0.95	137	1	13	2.09	98.5
Aug '04	75	7.5	101	0.98	134	2	19	0.53	98.4
Sept '04	65	6.8	94	0.99	147	2	17	1.08	98.9
Oct '04	65	6.7	96	0.97	147	5	16	1.46	99.3
Nov '04	76	7.2	100	0.95	147	9	11	1.06	98.6
Dec '04	48	4.4	101	0.96	104	5	9	1.78	98.8
Jan '05	83	8.1	102	0.95	158	3	14	0.87	98.0
Feb '05	72	8.0	99	0.99	158	7	8	1.16	98.5
Mar '05	74	8.6	91	0.98	161	6	13	1.25	98.9
Apr '05	76	7.1	86	0.80	147	10	19	1.24	99.1
May '05	68	8.2	95	0.99	147	11	5	0.69	99.0
June '05	58	6.5	96	0.97	140	1	16	0.20	99.1
July '05	73	7.6	95	0.99	147	12	11	1.23	99.6
Aug '05	87	9.5	97	0.98	177	9	15	0.62	98.5
Sept '05	73	7.6	92	0.99	154	10	15	0.69	98.8
Oct '05	75	8.1	87	0.98	164	2	13	2.62	99.2
Nov '05	74	8.1	100	0.99	154	1	12	1.65	99.0
Dec '05	27	4.7	99	0.99	89	2	9	0.00	99.2

TABLE A.2

RAW DATA FOR THE CURRENT PRODUCTION DATA SET

DMU	Batches (#)	Actual units (mm)	Standard (%)	On-time release	Shifts (#)	Reworks (#)	Exceptions (#)	Units resampled (%)	Material exception free (%)
Jan '06	91	7.8	87	0.99	170	3	12	3.12	99.3
Feb '06	75	7.8	94	0.97	147	1	17	0.65	99.0
Mar '06	79	9.3	89	0.99	170	4	16	0.41	98.9
Apr '06	78	7.9	95	0.99	154	3	16	0.13	98.9
May '06	82	8.9	92	0.98	169	4	8	0.56	98.6
June '06	60	7.4	92	1.00	129	8	6	2.86	99.3
July '06	89	9.9	97	1.00	164	3	8	0.85	99.2
Aug '06	87	11.1	100	1.00	200	2	16	0.54	98.6
Sept '06	71	9.2	100	0.96	166	1	13	0.13	99.2
Oct '06	85	9.6	97	0.96	188	3	14	3.98	98.6
Nov '06	82	8.7	100	0.97	172	1	8	0.94	98.2
Dec '06	46	4.6	100	0.93	98	0	13	0.89	98.2

TABLE A.3

EFFICIENCY SCORES FOR THE HISTORICAL PRODUCTION DATA SET

DMU	Efficiency Score
Jan '03	1.000
Feb '03	0.918
Mar '03	0.925
Apr '03	0.951
May '03	0.967
June '03	0.964
July '03	0.999
Aug '03	0.962
Sept '03	0.997
Oct '03	0.999
Nov '03	0.981
Dec '03	1.000
Jan '04	1.000
Feb '04	0.995
Mar '04	1.000
Apr '04	1.000
May '04	0.973
June '04	1.000
July '04	1.000
Aug '04	1.000
Sept '04	0.993
Oct '04	0.974
Nov '04	0.984
Dec '04	1.000
Jan '05	1.000
Feb '05	1.000
Mar '05	0.990
Apr '05	0.927
May '05	1.000
June '05	1.000
July '05	0.994
Aug '05	1.000
Sept '05	1.000
Oct '05	0.989
Nov '05	1.000
Dec '05	1.000

TABLE A.4

INDIVIDUAL WEIGHTS FOR THE HISTORICAL PRODUCTION DATA SET

DMU	Batches (#)	Actual units (mm)	Standard (%)	On-time release	Shifts (#)	Reworks (#)	Exceptions (#)	Units resampled (%)	Material exception free (%)
Jan '03	0.926	0.020	0.025	0.030	0.334	0.027	0.207	0.401	0.031
Feb '03	0.056	0.000	0.000	0.862	0.048	0.000	0.004	0.000	0.948
Mar '03	0.000	0.000	0.000	0.925	0.000	0.002	0.009	0.000	0.989
Apr '03	0.013	0.000	0.000	0.938	0.000	0.001	0.000	0.000	0.999
May '03	0.967	0.000	0.000	0.000	0.000	0.032	0.102	0.000	0.866
June '03	0.010	0.000	0.000	0.954	0.030	0.000	0.009	0.000	0.961
July '03	0.000	0.000	0.000	0.999	0.000	0.005	0.008	0.000	0.987
Aug '03	0.000	0.240	0.722	0.000	0.000	0.000	0.001	0.000	0.999
Sept '03	0.058	0.000	0.000	0.938	0.046	0.001	0.002	0.000	0.951
Oct '03	0.040	0.000	0.000	0.959	0.000	0.000	0.000	0.000	1.000
Nov '03	0.012	0.000	0.000	0.969	0.000	0.001	0.000	0.000	0.999
Dec '03	0.017	0.017	0.924	0.041	0.749	0.166	0.031	0.013	0.042
Jan '04	0.691	0.172	0.068	0.069	0.896	0.000	0.006	0.028	0.070
Feb '04	0.000	0.086	0.157	0.752	0.090	0.000	0.007	0.000	0.904
Mar '04	0.621	0.117	0.128	0.134	0.530	0.000	0.079	0.259	0.133
Apr '04	0.002	0.993	0.002	0.002	0.002	0.031	0.122	0.002	0.844
May '04	0.000	0.758	0.215	0.000	0.587	0.008	0.027	0.000	0.378
June '04	0.003	0.003	0.017	0.977	0.003	0.001	0.003	0.002	0.991
July '04	0.822	0.049	0.062	0.068	0.840	0.006	0.042	0.043	0.070
Aug '04	0.849	0.043	0.054	0.054	0.863	0.009	0.047	0.027	0.054
Sept '04	0.001	0.000	0.000	0.992	0.000	0.000	0.000	0.007	0.993
Oct '04	0.000	0.000	0.085	0.889	0.000	0.002	0.000	0.000	0.998
Nov '04	0.022	0.000	0.780	0.182	0.068	0.000	0.012	0.007	0.913
Dec '04	0.003	0.000	0.000	0.775	0.003	0.000	0.001	0.000	0.005
Jan '05	0.950	0.015	0.018	0.017	0.016	0.066	0.256	0.368	0.294
Feb '05	0.006	0.096	0.455	0.443	0.007	0.005	0.011	0.012	0.965
Mar '05	0.000	0.115	0.000	0.875	0.080	0.000	0.000	0.000	0.920
Apr '05	0.565	0.362	0.000	0.000	0.652	0.000	0.000	0.000	0.348
May '05	0.014	0.001	0.001	0.984	0.035	0.001	0.005	0.000	0.958
June '05	0.205	0.210	0.286	0.299	0.239	0.147	0.223	0.085	0.305
July '05	0.063	0.000	0.000	0.931	0.052	0.000	0.003	0.000	0.946
Aug '05	0.931	0.024	0.022	0.023	0.600	0.018	0.192	0.167	0.023
Sept '05	0.017	0.002	0.002	0.979	0.002	0.002	0.002	0.012	0.982
Oct '05	0.068	0.000	0.000	0.921	0.000	0.001	0.009	0.000	0.990
Nov '05	0.063	0.002	0.183	0.753	0.006	0.000	0.003	0.001	0.989
Dec '05	0.618	0.077	0.150	0.155	0.755	0.026	0.064	0.000	0.155

TABLE A.5

AGGREGATE WEIGHTS FOR THE OUTPUT AND INPUT VARIABLES

Variables	Aggregate Weight
Batches (#)	0.239
Actual Units (mm)	0.094
Standard (%)	0.121
On-time release (%)	0.525
Shifts (#)	0.209
Reworks (#)	0.015
Exceptions (#)	0.041
Units resampled (%)	0.040
Material exception free (%)	0.667

TABLE A.6

EFFICIENCY SCORES USING AGGREGATE WEIGHTS FOR THE HISTORICAL PRODUCTION DATA SET

DMU	Efficiency Score
Jan '03	0.300
Feb '03	0.286
Mar '03	0.255
Apr '03	0.264
May '03	0.293
June '03	0.263
July '03	0.279
Aug '03	0.298
Sept '03	0.296
Oct '03	0.304
Nov '03	0.282
Dec '03	0.236
Jan '04	0.332
Feb '04	0.304
Mar '04	0.310
Apr '04	0.326
May '04	0.305
June '04	0.286
July '04	0.336
Aug '04	0.332
Sept '04	0.288
Oct '04	0.290
Nov '04	0.324
Dec '04	0.279
Jan '05	0.338
Feb '05	0.307
Mar '05	0.299
Apr '05	0.303
May '05	0.299
June '05	0.277
July '05	0.309
Aug '05	0.328
Sept '05	0.302
Oct '05	0.294
Nov '05	0.315
Dec '05	0.228

TABLE A.7

EFFICIENCY SCORES USING AGGREGATE WEIGHTS FOR THE CURRENT PRODUCTION DATA SET

DMU	Efficiency Score
Jan '06	0.328
Feb '06	0.313
Mar '06	0.304
Apr '06	0.318
May '06	0.316
June '06	0.285
July '06	0.342
Aug '06	0.318
Sept '06	0.300
Oct '06	0.316
Nov '06	0.325
Dec '06	0.278

TABLE A.8

ANALYSIS OF VARIANCE OF PERFORMANCE SCORES FOR THE HISTORICAL PRODUCTION DATA SET

Analysis of Variance for DEA Metric - Type III Sums of Squares

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
MAIN EFFECTS					
A:Month	0.0132256	11	0.00120233	5.77	0.0002
B:Year	0.00556436	2	0.00278218	13.35	0.0002
RESIDUAL	0.00458519	22	0.000208418		
TOTAL (CORRECTED)	0.0233751	35			

TABLE A.9

MULTIPLE RANGE TESTS FOR PERFORMANCE SCORES BY MONTH

Multiple Range Tests for DEA Metric by Month

Method: 95.0 percent LSD

Month	Count	LS Mean	LS Sigma	Homogeneous Groups
Dec	3	0.24762	0.00833502	X
June	3	0.275376	0.00833502	X
Mar	3	0.288161	0.00833502	XX
Sept	3	0.295281	0.00833502	XXX
Oct	3	0.295854	0.00833502	XXX
Apr	3	0.297769	0.00833502	XXX
May	3	0.299018	0.00833502	XXXX
Feb	3	0.299096	0.00833502	XXXX
Nov	3	0.306865	0.00833502	XXX
July	3	0.307658	0.00833502	XXX
Aug	3	0.319491	0.00833502	XX
Jan	3	0.323461	0.00833502	X

TABLE A.10

MULTIPLE RANGE TESTS FOR PERFORMANCE SCORES BY YEAR

Multiple Range Tests for DEA Metric by Year

Method: 95.0 percent LSD

Year	Count	LS Mean	LS Sigma	Homogeneous Groups
1	12	0.279591	0.00416751	X
3	12	0.299933	0.00416751	X
2	12	0.309389	0.00416751	X

APPENDIX B

FIGURES

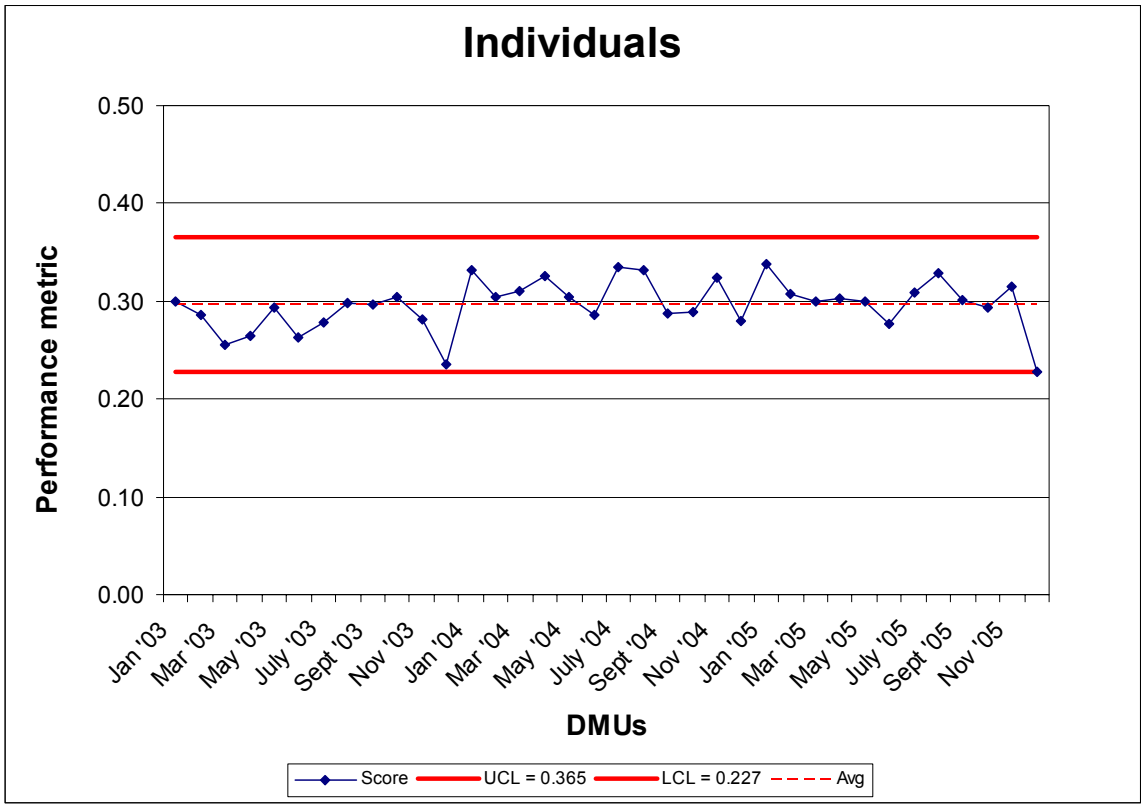

FIGURE B.1
INDIVIDUALS – HISTORICAL PRODUCTION DATA SET

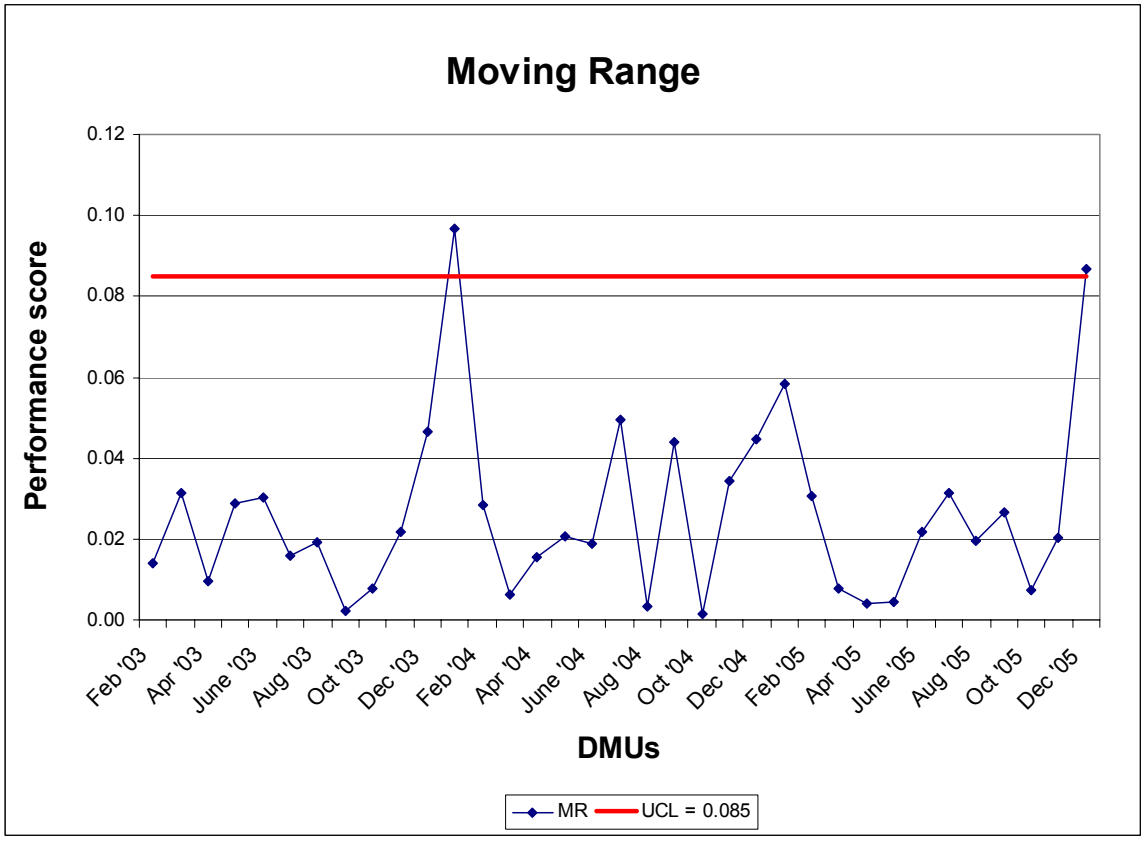

FIGURE B.2
MOVING RANGE – HISTORICAL PRODUCTION DATA SET

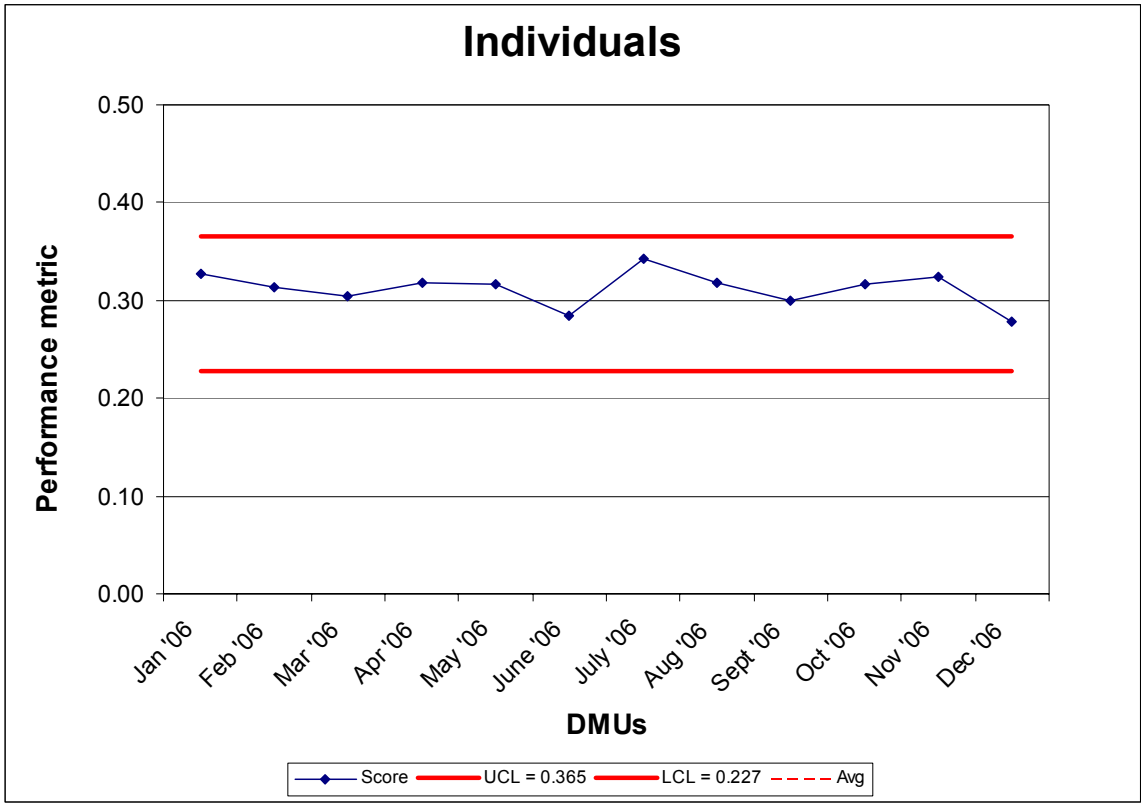

FIGURE B.3
INDIVIDUALS – CURRENT PRODUCTION DATA SET

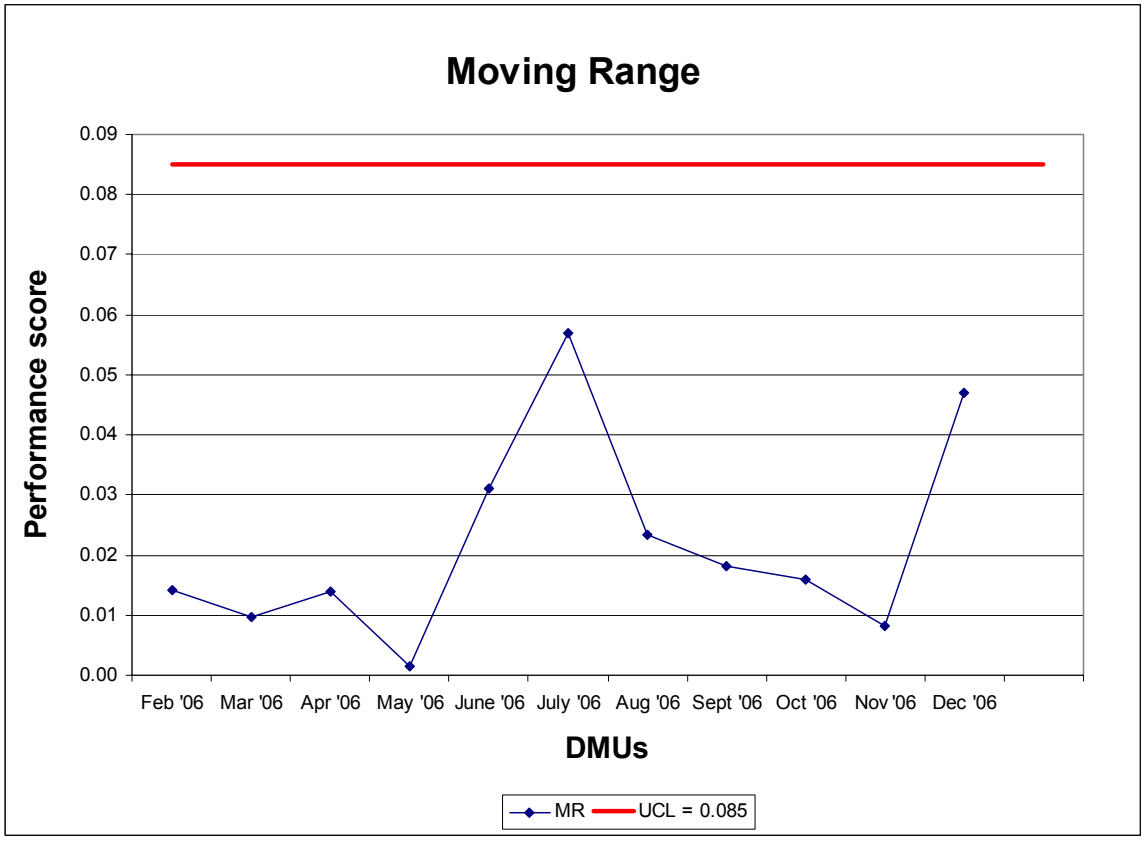

FIGURE B.4
MOVING RANGE – CURRENT PRODUCTION DATA SET

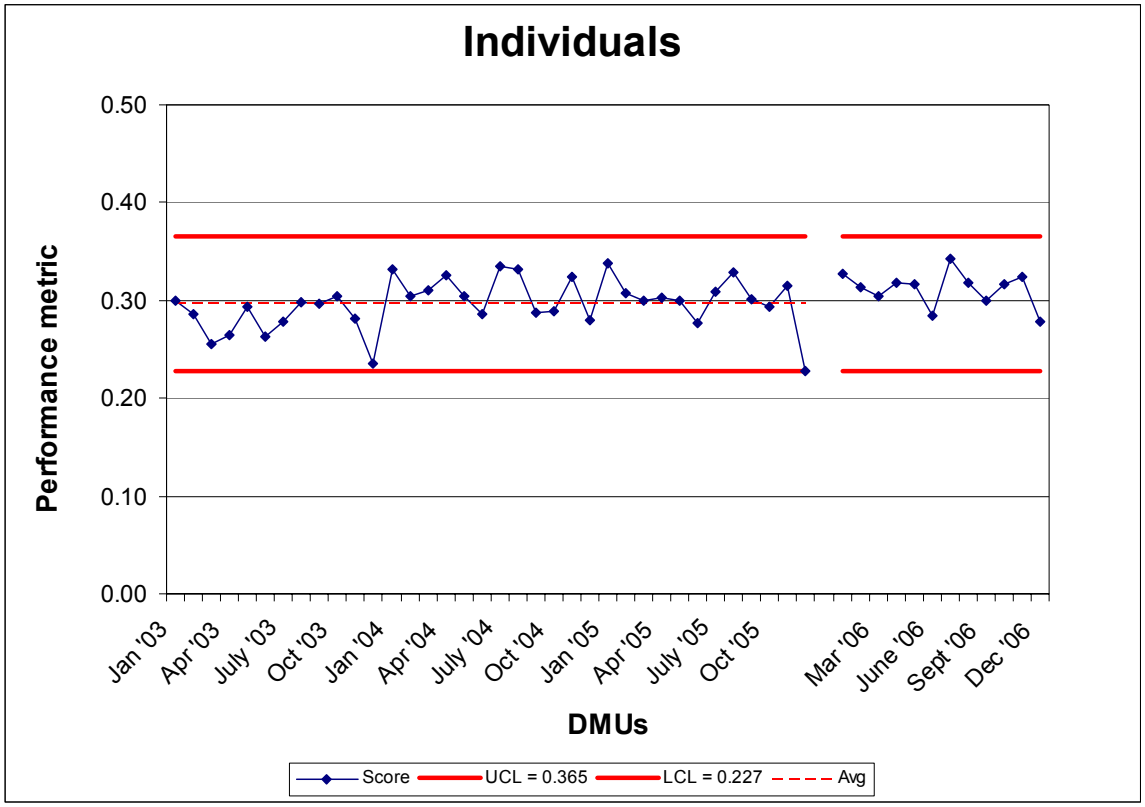

FIGURE B.5
INDIVIDUALS – SIDE BY SIDE COMPARISION

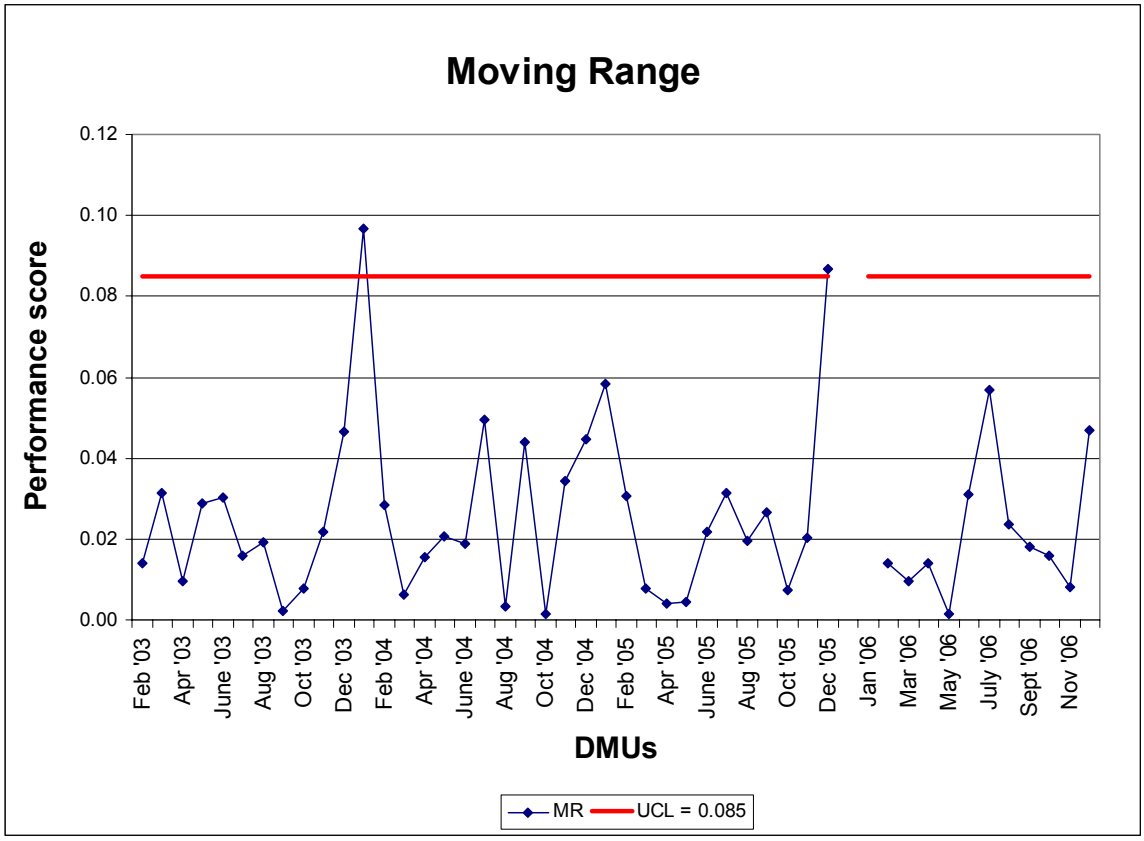

FIGURE B.6
MOVING RANGE – SIDE BY SIDE COMPARISON

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BIOGRAPHICAL INFORMATION

Angela BenBarka has worked in private industry in the Quality Assurance field for the past 13 years. She has held positions as Quality Engineer, Q.A. Supervisor, Compliance Analyst, and Project Manager. Notable accomplishments have included development of a training program for Q.A. inspectors, establishment of control limits for new production processes, sampling reduction plan for on-line monitoring, and implementation of SPC data collection system for manufacturing systems. Angela earned a Bachelor of Science in Mathematics degree at the University of Texas at Arlington and holds ASQ Quality Technician and Quality Engineering certifications.