Illustration of *Six Sigma** Assistance on a Design Project

Pierre Bayle, Mike Farrington, and Brenner Sharp
Whirlpool Corporation

Cheryl Hild and Doug Sanders
Six Sigma Associates

Key Words: Six Sigma, statistical methods, design engineering, analytical modeling, simulation, design of experiments (DOE)

Abstract

Organizationally, for Six Sigma types of approaches to be sustainable, there must be an awareness that statistical methods are most useful when engineering theory, process and product knowledge, and statistical thinking and methods are merged. The authors illustrate this truth via a project discussion on the design and development of a brake subsystem for a new product. This project is used to clearly illustrate the role of statistical methodologies in facilitating the design process by validating engineering theory and providing scientific, empirical feedback to the designers. Just as importantly, the case study is used to discuss the boundaries of the contributions that statistical methodologies can provide and the criticality of engineering theory in product design.

---

* Six Sigma is a registered trademark of Motorola, Inc.

Published Quality Engineering 2001 13(3)

Introduction

As the use of *Six Sigma* (6σ) initiatives proliferates, organizational strategies, concepts and even tools become more and more variable. This variety is potentially positive, as it would be unreasonable to think a single deployment strategy would be effective across all organizations equally or that only one set of tools is needed regardless of process or product. The choice of deployment strategy and appropriate methodologies should be guided by organizational and project needs. "In its ideal formulation, the content of 6σ as a process is built around the creative union of managerial objectives for process or product, confirming and expanding engineering and operational knowledge, and the practical and immediate application of basic and advanced statistical procedures."[1]

Organizationally, for *Six Sigma* types of approaches to be sustainable, there must be an awareness that statistical methods are most useful when engineering theory, process and product knowledge, and statistical thinking and methods are merged. Too often, in statistical training and application, there is over reliance on modeling and an insufficient emphasis placed on engineering and product knowledge. A common belief is that statistical models (and other methods) can transform poor engineering knowledge and practice into useful information. This is rarely the case.

> Statistical methodologies are not a replacement for the application of engineering principles or knowledge of the underlying physics of the system.

Illustrated via the brake subsystem design project described in this article, this truth is seen throughout the product design and Research and Development (R&D) arenas. Both in the development of new concepts as well as the optimization of existing products or processes, the focus of the work should be on knowledge acquisition and validation. An emphasis on knowledge drives questions and theories that, in turn, are invalidated or supported by information. This information, obtained through the thoughtful acquisition of data and subsequent analysis, generates new insights, questions and theories. As illustrated by Hild and Sanders[2] in Figure 1, the learning cycle is repeated as many times as required to obtain sound, validated, and sustainable solutions.

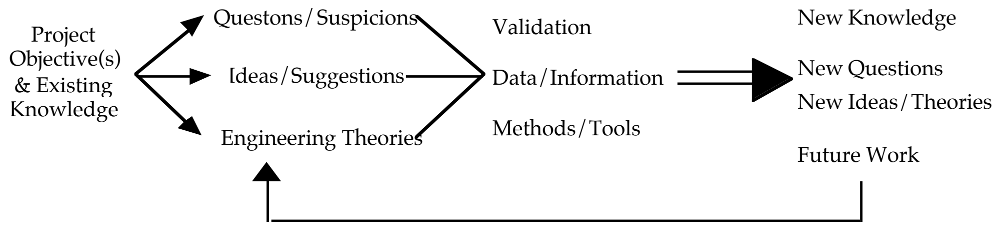

Figure 1: The learning cycle (From Ref. 2)

Project: The Design and Optimization of a Braking Subsystem•

The project objective was to design and optimize the braking subsystem for a new product at Whirlpool Corporation. The purpose of the subsystem is to stop a rotating part within a specified amount of time. Although the overall project was extensive in content, involving many parallel paths of work, two key paths are utilized to illustrate the role of Six Sigma as the effective blending of statistical methodologies, engineering theory, and product knowledge.

Prototypes of past designs had exhibited two distinctive behavior patterns:

1. A "common cause"[3] system of causal factors, resulting in excessive brake time variation from machine to machine. Some prototype machines failed to brake within the government regulatory requirement, while others had such fast brake times that forces were produced that the machines were not designed to handle.
2. Erratic sources of variation resulting in unexplainable occurrences in which past prototype brake units failed to actuate at all (referred to as "coasting").

Hence, the two parallel paths of work focus on gaining knowledge about two very different causal structures acting on the system. The simplified thought map shown in Figure 2 summarizes these two paths.

• The authors are greatly appreciative of the contributions made by all members of the brake project team. These individuals include S. Amos, B. Balinski, R. Evans, M. Giddings, K. Lahrman, D. Selvidge. S. Fricke, T. Judd and S. Morenelli. Additionally, we appreciate the support of Vic Vukorpa, Design Manager.

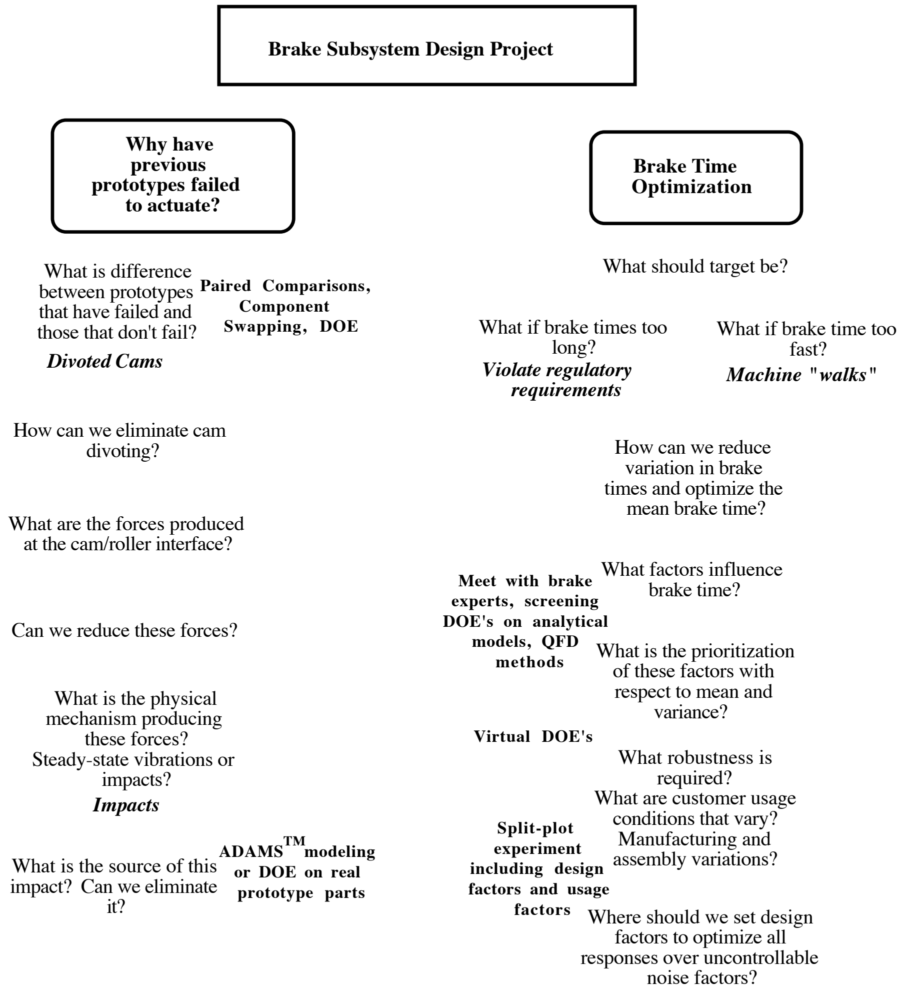

Figure 2: Summary thought map of two parallel paths of work.

The project was critical and urgent, as other component designs for the new product were complete or close to completion. Failure to deliver a workable brake subsystem design on time would prevent the entire product from going into production. Because some tooling was already released, it was preferable for the work to be done within the existing brake concept. The time requirements were also very restrictive.

The team of engineers assigned to this project had little knowledge concerning the specifics of braking systems. However, they were strong in their knowledge of physics and applicable engineering principles. Additionally, as a result of an ongoing Six Sigma training and deployment initiative at Whirlpool, many of the engineers were trained in Six Sigma concepts and methodologies. Additional laboratory, consultant, and virtual engineering resources were heavily utilized to augment the expertise of the team.

Project Path One: Understanding Causes of Erratic Actuation Failures

The major objective associated with this path was to understand why the brakes on some prototype units failed to actuate at all. Observations of past prototype units that failed to actuate focused attention on the cam component. (The cam was used to control the location of the brake shoes relative to the brake drum.) Localized, permanent deformation in the cam (i.e., divoting) apparently caused the rollers on the cam surface to stop or "stick in place", preventing brake actuation.

The discussion of potential causal mechanisms led to the consideration of many physical properties of the brake subsystem, including driving torque, part dimensions, assembly constraints, and boundary dimensions. Additionally, it was realized that there was a host of response variables that needed to be measured in order to understand specifically the cam failure. Forces at any and all locations as well as cam angle versus time profiles were potential critical responses. Given that very little was known about the mechanisms causing the failure, it was not obvious which responses and physical properties were most relevant. Hence, it seemed impossible to isolate or prioritize all of the potential contributing factors and response variables listed on the product map[4]. As a result, the team needed to be able to measure a large number of responses, such as forces at every location. Given these facts and time constraints, it was even more obvious to the team that it would be impractical to screen statistically (and iteratively) factors and responses on real prototype parts.

A simulation model was developed in ADAMS™[*] to simulate the forces and movements of the components in the brake system. This analytical model provided two key advantages: (1) the ability to obtain measurements on a large set of responses, and (2) much quicker responses than could be obtained by building prototype parts and testing them.

---

[*] ADAMS is a registered trademark of Mechanical Dynamics, Inc.

Unfortunately, in spite of all of the knowledge and theory that went into the development of the simulation model and the large amounts of information provided by the model, initial investigative probes using the simulation failed to provide new insights or adequate explanations for the actuation failures. To gain insights into the underlying physics of the system, new questions focused on the possible effect of design factors, interactions among the variables, and the effect of uncontrollable noise variables on the various responses. Perhaps due to the statistical training, a design of experiments (DOE) was considered to be the most efficient way to develop knowledge about potential answers to these questions. Hence, the team decided to merge expertise in braking systems, engineering and physical principals, and simulation modeling with the concepts behind statistically designed experiments. The strategy paid off.

> Key Learning 1: It is extremely tempting to interrogate simulation/computer models using the same trial-and-error or one-factor-at-a-time methods that are well known to be inefficient and ineffective in process and product studies. These "poke and probe" techniques build very little intuition and are often misleading.

A two-level, fractional factorial experiment was run on the analytical model. Two of the responses, angular position of the cam and force variation in the cam-roller interface, clearly showed a strong correlation. Although this correlation was unexpected, when carefully interpreted from an engineering perspective, it provided great insights into the causes of actuation failure.

The angular position of the cam determines the location of the brake shoes relative to the drum. Movement in the cam after the brake is deactivated can possibly result in the shoes contacting the drum while the motor is still driving the rotating part. This contact would cause the large force variations seen in the cam-roller interface. Such engineering considerations allowed the team to safely conclude that the observed correlation between the responses did in fact imply causation for the observed failure mode. Thus, if the angular position of the cam could be controlled, the forces could be eliminated and the cam failure avoided.

> Key Learning 2: Too often, we use models and experimental designs to "prove the obvious". It is often the unexpected results that provide the greatest insights into potential engineering solutions.

The observed correlation in responses led to the need to gain insights concerning factors that could be used to control the angular position of the cam. The DOE analysis provided the needed clues. Two factors, DRAG and FORCE, showed to have the strongest effects on the angular position of the cam. The statistical analysis suggested design changes that favored a higher DRAG and a lower FORCE. Even though the DOE clearly showed that these factors have strong effects on the primary response of interest, the team could not determine immediately why from an engineering perspective. Additionally, this combination of factors, as recommended by the statistical analysis, was physically impossible to implement. DRAG was uncontrollable from an engineering viewpoint. (Engineers rarely rely on friction to resolve an issue.) At the same time, FORCE was set to meet other design constraints.

While implementation of experimental results (i.e., setting DRAG high and FORCE low) was not practical or feasible, the team chose to question more thoroughly the clues provided by the DOE. *Why did these two factors have such a strong impact on the critical responses?* Via much discussion, questioning, and theorizing, the engineers came to the realization that the relationship being exhibited by the factor effects in the DOE was not directly between the two forces themselves, but between the *torques* (a function of force and distance) associated with each of the two factors. Given that force is equal to torque divided by distance, this new theory led to a change in specifications for the cam design. Torque could be manipulated via change in cam geometry without sacrificing the force itself associated with the cam.

> Key Learning 3: Decisions based on purely statistical considerations can often yield changes that are infeasible or far from optimal. Only through critiquing and questioning statistical results from a subject matter and engineering point of view are true underlying causal structures really understood.

Project Path Two: Brake Time Variation Reduction

As shown on the thought map of Figure 2, a second path that was worked in parallel with the "coasting" issue was brake time optimization and variation reduction. As previously stated, earlier prototype units had exhibited excessive amounts of brake time variation. In order to optimize brake times and reduce variation, the team developed a timeline to meet production schedule (shown in Fig. 3). Weeks of prototype tooling time would have been

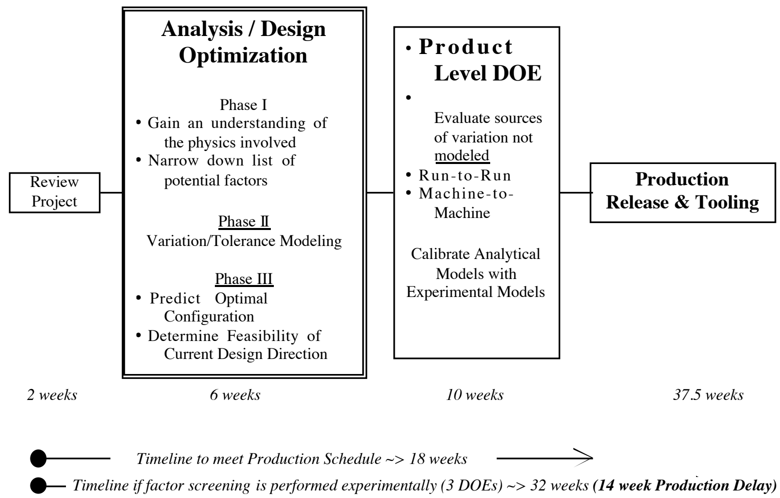

Figure 3: Project plan for brake time variation reduction and optimization.

needed to complete multiple designed experiments on prototype parts. Therefore, a decision was made to use simulation modeling as a means to bring the design within a moderate distance of optimal performance. Then, designed experiments on real prototype parts could be used to confirm insights gained, to assess the effect of certain noise factors, and to optimize the brake design.

Phase I: Development of Insights into Factors and Responses

In order to utilize simulation models to develop an initial product design with needed performance characteristics, it was necessary to rely heavily on the physics of the initial design concept. Thus, for the first few weeks, the team needed to develop deeper insights into the physics of the initial brake subsystem concept, including response variables to measure and potential factors to include in the simulations. Through consultation with external experts on brake design, review of experiences with previous prototypes, and incorporation of engineering principles, the team generated a set of response variables and potential factors. This initial list included at least seven key response variables and 34 possible factors.

Quality Function Deployment (QFD) methods[5] were used to prioritize the list of factors and to categorize them in terms of the response variables they were most likely to effect. The team also used this work to organize the different models that had to be created for the different response variables. The team identified 12 factors possibly affecting brake times. Subsets of these 12 factors would be included in 4 different simulation models. The team also spent time identifying potential noise factors (e.g., manufacturing and raw material variations) that could potentially impact the responses.

> Key Learning 4: In order to develop useful models, it is necessary to predict and prioritize factor effects, their interactions, and potential noise factors across multiple response variables. Without such knowledge and insights, many models provide a prolific amount of data and results that do not provide specific guidance with respect to the critical questions that need to be answered.

Phase II: Determination of Design Configuration and its Feasibility

There were three main stages of work in the design analysis phase. These stages involved the following:

1. Screening of factors
2. Evaluating the effect of variation in factor levels around their nominal values
3. Searching of all response surfaces for an optimal design.

Two virtual DOEs were performed to acquire the knowledge needed to plan a product-level experiment on real prototype parts. A screening DOE was run on a simulation model (developed in ANSYS^{TM*}) to understand the effects of forces on deflection, pressure distributions, and brake torques. This study helped the team to screen from the original set of 12 factors a subset of eight factors to include in future studies. In addition to focusing future work, the analysis of the ANSYS model showed that small deflections in drum roundness had little effect on dynamic brake forces. This knowledge suggested little need for work to focus on changing the brake drum design. This result was much appreciated, as the tooling for the brake drum had already been released.

> Key Learning 5: Too often, in analyzing statistical studies, focus is placed on the factors that have the strongest effects on the response of interest. There is as much information

* ANSYS is a finite-element analysis software owned by ANSYS, Inc.

and insight provided about direction for future work by considering the implications of factors with little or no effect.

With the new insights and the reduced set of factors, the team now needed to understand the effect of manufacturing and assembly variations. A model in MECHANICAL ADVANTAGE™* allowed the team to study the effect of variations in the design parameters as permitted on the toleranced drawings. A DOE was run on this model to understand the effect of eight design factors on the mean and variation in brake times. The experiment proved useful for predicting the capability of particular design configurations. With the available information, the team was able to validate the decision between optimizing the current brake concept or developing an entirely new brake subsystem concept early in the project.

The team now focused on optimizing design factors on the current brake system to achieve the desired reduction in variation and optimization of brake times. Level settings on the eight factors were studied (using the SOLVER† optimization routine) in terms of their effects on brake time mean and variation, cam torque, and other metrics. Figure 4 shows the resulting predicted improvement in terms of the robustness of the prototype design configuration on the primary response of interest.

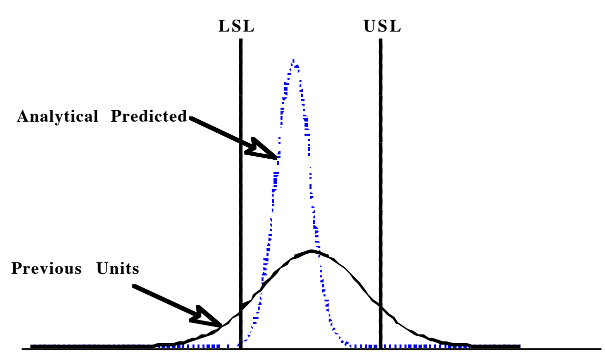

FIGURE 4: Simulation Results Showing Predicted Improved Robustness with Respect to Primary Response Metric

---

* MECHANICAL ADVANTAGE is a registered trademark of Cognition Corporation.

† SOLVER is available in Microsoft EXCEL spreadsheet applications.

Phase III: Product Level DOE

As a result of the first two phases of work, the team had a predicted optimum design as well as a set of eight factors believed to be influential across the critical response variables. In addition to validating the optimum design predicted in the analytical portion of the project, important questions that needed to be answered dealt primarily with the effect of components of variation that were not captured explicitly in the experiments on the simulation models. An experimental design on prototype parts using centerpoints was planned in order to provide insights into the following:

- The possibility of effects over time of background noise variables
- Machine-to-machine and within-machine run-to-run variation
- The curvature of the response surface and adequacy of the model.

Parts were tooled to represent the two levels of each factor recommended from the simulation phases of work. A separate machine was built to represent each of the 16 treatment combinations in the experiment. The optimum design (predicted from the analytical studies) was used as a centerpoint for the experiment. Four additional units were built in order to run centerpoints over the course of the experiment. It was also planned to test each machine under varying noise conditions, representing potential variations in customer usage. Hence, a split-plot experiment was run with a fractionated whole-plot portion containing the design factors and the split-plot containing the noise factors.

The first thing that the experiment provided was a quantification of the effects of the noise (i.e., customer usage) factors and noise by design factor interactions. Using these effects, the team was able to obtain an estimate of expected variation in brake time due to customer use. This estimate was then added to the machine-to-machine and run-to-run estimates of variation obtained using the centerpoint units. Secondly, the experiment provided a mean response surface that could be used to find the optimum settings for the design parameters. Using the total variance estimate and the predicted mean, the response surfaces were searched to find the optimum settings across the design parameters.

Key Learning 6: An experimental study can capture components of variation that are not understood or explained, whereas an analytical, simulation study only contains sources of variation that are specifically injected into the study.

Results

Once the new design was placed in actual machines, the brake actuation failures that occurred on previous prototypes disappeared. The variation in the brake times was also dramatically reduced. However, the design configuration predicted to be optimum in the simulation studies (represented by the four centerpoint units) showed slightly shorter brake times than what was predicted. The information from the product level DOE allowed the team to adjust the actual design configuration for this discrepancy. The design was then tooled and placed on 85 machines for validation and confirmation. The resulting performance mirrored the original predicted optimum nicely. Brake times on the 85 machines all remained below the specification established in government regulations. Additionally, the team was able to reduce variation in brake times to eliminate unacceptably fast brake times. These results are shown in Figure 5.

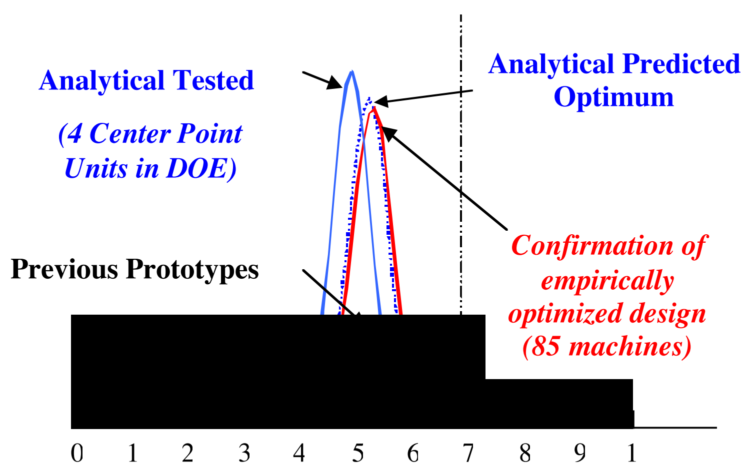

FIGURE 5. Resulting Performance of Brake Design

Summary

The use of statistical tools, simulations and engineering knowledge all played key roles in the success of this design project:

- Without the analytical (simulation) models, the team could not have feasibly measured the multiple responses needed to understand the underlying physics and causal structures. It would have been impossible to collect data and run experiments over a sufficient number of prototype units to screen response variables, understand factors and optimize the design configuration in such a short time frame.
- Without statistical methods, unknown sources of variation acting on the system (e.g., customer usage practices) could not have been understood. The statistical methods provided an efficient way of sampling the response surfaces generated by the analytical models in order to generate new insights.
- Without engineering knowledge, neither useful simulations nor experiments could have been developed. For example, the DOE analysis of the cam-roller forces would have only provided clues and hints, but no actionable factors. The team could not have understood the real failure mechanism that was taking place and would have been incapable of identifying a solution.

Conclusion

In its most effective form, Six Sigma is not a roadmap or a set of tools. It is an appropriate *blending* of tools, methods, and expertise (as determined by the questions that need to be answered) in order to obtain long-term solutions efficiently. Engineering knowledge and practice is the foundation/basis for the use of any set of tools. The data acquisition plan, the factors to be included in the study, the choice of analysis technique, and the interpretation of results are entirely dependent on sound engineering theory and practice.

The usefulness of Six Sigma methodologies in product design and development efforts lies in the validation (or invalidation) of current theory and practice and in the encouragement of improved theories. The chasm between proposed engineering solutions and statistical thinking and methods is bridged when data acquisition is focused on gaining new knowledge and understanding the viability of engineering solutions over changing noise conditions.

Once knowledge on relationships is available, the design or solution *always* becomes an engineering or managerial one. Thus, the permanency of any engineering/managerial solution is directly correlated to the level of knowledge. Statistical and analytical modeling tools are only facilitators and expeditors in the confirmation and expansion of engineering knowledge. As seen throughout the brake subsystem development project, the successful use of statistical tools and simulation models to study and improve a design or system is predicated on the need for sound engineering theories and physical principles to guide the work. Shewhart[6] shared such wisdom on the role of statistical methodologies years ago:

> The long-range contribution of statistics depends not so much upon getting a lot of highly trained statisticians as it does it creating a statistically minded generation of physicists, chemists, engineers, and others who will in any way have a hand in developing and directing the production processes of tomorrow.

References and Endnotes:

1 Sanders, D. and Hild, C., A Discussion of Strategies for the Implementation of Six Sigma, *Quality Engineering*, 12(3) pp. 303-309, (2000).

2 Hild, C. and Sanders, D., The Thought Map, *Quality Engineering*, 12(1) pp.21-27 (2000).

3 Deming, W. E., *Out of the Crisis*, Massachusetts Institute of Technology, Cambridge, MA, 1986.

4 Sanders, D., Ross, B. and Coleman, J., The Process Map, *Quality Engineering*, 11(4) pp. 555-561, (1999).

5 Mizuno, S. and Akao Y., Quality Function Deployment – An Approach to CWQC, J.U.S.E. (1978).

6 Shewhart, W. A., *Statistical Methods from the Viewpoint of Quality Control*, Dover, New York, 1986.