Design of Experiments for Non-Manufacturing Processes: Benefits, Challenges and Some Examples

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Abstract

Design of Experiments (DoE) is a powerful technique for process optimization that has been widely deployed in almost all types of manufacturing processes and is used extensively in product and process design and development. There have not been as many efforts to apply powerful quality improvement

techniques such as DoE to improve non-manufacturing processes. Factor levels often involve changing the way people work and so have to be handled carefully. It is even more important to get everyone working as a team. This paper explores the benefits and challenges in the application of DoE in non-manufacturing contexts. The viewpoints regarding the benefits and challenges of DoE in the non-manufacturing arena are gathered from a number of leading academics and practitioners in the field. The paper also makes an attempt to demystify the fact that DoE is not just applicable to manufacturing industries; rather it is equally applicable to non-manufacturing processes within manufacturing companies. The last part of the paper illustrates some case examples showing the power of the technique in non-manufacturing environments.

Introduction

Design of Experiments (DoE) sometimes called Multifactor testing (MFT) is fundamental and crucial to increase the understanding of a product or process. It provides a powerful means to achieve breakthrough improvements in product quality and process efficiency. According to Montgomery (2009), DoE is a powerful tool which enables the effects of several system or process variables to be investigated simultaneously and efficiently leading to an increased understanding of the system. DoE is a direct replacement of the traditional one-factor-at-a-time (OFAT) or “hit or miss” approach to experimentation and the sequential testing approach of Shainin. [see Antony (1998) and Shainin and Shainin (1988)].

DoE has been widely applied to various problems in the manufacturing arena, but little attention has been paid to its applications in the context of non-manufacturing. Although it has been around for decades, few business leaders in service organizations have a good grasp of its power in tackling problems associated with service process efficiency and effectiveness [Johnson and Bell, (2009)]. This field remains fertile ground for greater education, experience and application. Service oriented industries such as financial services, transportation services, hotel and restaurant services, healthcare industry, utility services, IT services etc. are the fastest growing sectors around the world [Kapadia and Krishnamoorthy (1999)]. Customers are becoming more critical of the service they receive today and therefore most modern organizations are paying more attention to their transactional service processes.

Our research has clearly indicated that relatively few applications of DoE in a non-manufacturing environment have appeared in the academic literature [Ledolter and Swersey (2006, Blosch and Antony (1999, and Kumar et al. 1996)]. This paper presents the benefits of DoE in non-manufacturing settings, the fundamental challenges encountered by practitioners in the application of DoE in non-manufacturing processes and provides examples that demonstrate the power of DoE in non-manufacturing settings.

Design of Experiments in non-manufacturing Industry: Fundamental Challenges

A product realization process initiated by the manufacturer, usually begins with product design and development, a set of product specifications, process development, then production and testing, and concludes with delivery to the customer. If at any point in the process products do not meet specifications, they can either be scrapped or reworked. Non-manufacturing or service processes on the other hand generate value as the customer interacts with the process and ultimately, it is the customers' experience with the process that is most important. The distinction between the process, the delivery of the process, and the customers' responses is often difficult to define. The exact sequence of activities in a non-manufacturing or service process is often difficult to predict in advance.

There are a number of reasons why DoE has not been commonly employed in non-manufacturing or service settings. We highlight some of the most fundamental barriers and challenges in applying DoE in a service environment. For more discussion see Roes and Dorr (1997) Raajpoot et al (2008), Holcomb (1994), Kumar et al. (1996), Johnson and Bell (2009), and Blosch and Antony (1999) .

- Lack of awareness, knowledge and misconceptions discourage experimentation in many service organizations.
- The performance of a service process is very difficult to measure accurately.
- Service process performance depends a great deal on the behaviour of the human beings involved in delivering it.

- Service processes have more “noise” factors associated with them (queuing, friendliness, location, politeness, etc.)
- As service is often simultaneously created and consumed and intangible dimensions are important indicators of quality on service context, experimental control of inputs and measurement of output requires careful consideration.
- In any service process, a clear description and distinction of service processes is needed for quality control and improvement. A good understanding of front office, back office and customer processes is required for quality and process improvements.

Table 1 was generated from a recent study carried out by the first author. A number of experts in the field of DoE (both academics and practitioners) were approached by the first author and the responses were collected over a period of 2 weeks. Each respondent was approached with a question “what are the fundamental challenges in the application of DoE in the non-manufacturing or service sector?”

Table 1 Challenges in the application of DoE in non-manufacturing or service settings

Respondents and their affiliations	Challenges
Kai Yang, Wayne State University, USA	• Cannot do too many trials of controlled tests in a service environment
Phil Rowe, Consultant and Six Sigma Master Black Belt, Bourton Group, UK	• people in the service sector are by and large not used to using/dealing with data-based decision-making • DoE is a ‘techy’ tool; managers in the service sector may be less likely to have a mathematical background and be perhaps more likely (than in engineering, say) to be driven by ‘experience’ and gut feel – wanting to be seen to be incisive and

	intuitive • Choosing the right response variables and dealing with subjectivity within the experimental regime.
Mark Anderson, Principal and General Manager, Stat-Ease, USA	• The involvement of people. Whereas a machine can be subjected to change with no trouble (provided its operating constraints are not exceeded), us humans resist new approaches to doing things
Larry Smith, Independent consultant, USA	• The biggest challenge is in determining what to measure and in finding operational control factors to conduct the DoE. It is also effective if a service process can be computer simulated so that the DoE may be done as a simulation.
Sung Park, Seoul University, South Korea	• The fundamental challenges are that it is not easy to obtain necessary observed data in the service sector, and also it is not easy to provide the same experimental condition for repeated measurement in the service sector.
Ronald Snee, Consultant, Tunnell Consulting, USA	• Lack of standardized work processes • Lack of improvement mindset • Greater amount of human intervention • Can be more difficult to administer the design properly and get quality data.
Alessandro Laureani, Master Black Belt, Hertz Services, Ireland	• As human factors are an important factor, randomization is necessary in the context of service. • As there is an intangible component with the delivery of service, results may not be as reliable as manufacturing. • Careful selection of factor levels is required due to involvement of people and the interaction between customer and service provider.
Roger Hoerl, General Electric, USA	• Personally, I think the cultural issues are greater. For one, there is rarely a culture of using the scientific method or applying continuous improvement in most service organizations. • Persuade people to follow a systematic methodology for process improvement and to convince them to rely on the power of data to drive the decision making process

The key question to be asked is “what do we need to do to encourage more applications of DoE in the non-manufacturing industry?” Due to the increasing applications of Six Sigma in both service and transactional processes, in particular, the finance, hotel, billing, invoicing, administrative processes and health sectors, we will likely see more applications of DoE in the improve phase of Six Sigma methodology. In the context of service, quality, speed and

cost are quite critical just as they are in manufacturing. Design of Experiments is a very powerful technique which can be employed by many non-manufacturing or service organizations to achieve a good balance between quality (that is improvement of service and product quality) and cost (that is reduction of operational costs) but also increase the speed with which the balance can be achieved. Table 2 shows how Six Sigma initiatives in the service sector can influence the deployment of DoE.

Table 2 The Influence of Six Sigma Initiatives in the Non-manufacturing or Service Sector on Deployment of DoE. [Adapted from Goh (2002)]

Aspect	Past	Future
Impetus	Operational level	Top management
Training provision	Stand-alone courses	Structured Company-wide programmes such as Six Sigma
Motivation of experimentation	Technical performance	Improved sales and enhanced customer satisfaction
Success criterion	Engineering objectives	Impact on the bottom-line in hard cash savings
Project ownership	Isolated individuals (industry statisticians, external consultants)	Multi-disciplinary teams across the business
Focus of application	Primarily manufacturing processes	Service, transactional and now governance processes
Project selection	Primarily projects are related to single functional problems	Projects are related to cross-functional problems

Benefits of DoE in Non-manufacturing/ Service Industry: A review of the Literature and Some Key Findings

The purpose of this section is to illustrate the benefits of DoE in various non-manufacturing/service settings. Our search for service applications of DoE has found a few papers in the marketing and service/retail industry literature. Holland and Cravens (1973) presented the essential features of fractional factorial design and illustrated a very interesting example looking into the effect of advertising and other critical factors on the sales of candy bars. Ledolter and Swersey (2006) described the power of a fractional factorial experiment to increase the subscriptions response rate of Mother Jones magazine. Kumar et al. (1996) used a Taguchi robust parameter design methodology in order to improve the response-time performance of an information group operation which was responsible for addressing customer complaints concerning a small software export company. Holcomb (1994) illustrated the use of Taguchi parameter design methodology to determine the optimal settings of customer service delivery attributes that reduce cost without affecting quality. Blosch and Antony (1999) demonstrated the use of computer simulation and DoE to identify the key risk variables within the manpower planning system at the UK's Royal Navy. This combined approach has provided a greater understanding of the manpower planning system, especially in terms of reducing gapping (a gap occurs when a particular job or task is not being filled by a competent and qualified person) at sea. Starkey et al. (1997) used a Plackett-Burman design in designing an effective direct response TV advertisement. Raajpoot et al. (2008) presented the application of Taguchi approach of DoE to retail service. The study was performed by under-graduate students at a mid-size University in the USA to determine the key attributes of shopping experience in a superstore setting such as Wal-

Mart or Target. Anderson (2009) has compiled a number of excellent examples. The potential applications of DoE in the non-manufacturing / service environment include:

- Identifying the key service process or system variables which influence the process or system performance
- Identifying the service design parameters which influence the service quality characteristics or CTQs in the eyes of customers
- Minimizing the time to respond to customer complaints
- Minimizing errors on service orders
- Reducing the service delivery time to customers (e.g.: banks, restaurants, etc.)
- Reducing the turn-around time in producing reports to patients in a healthcare environment, and so on.

Table 3 presents the potential benefits obtained from the applications of DoE in a service setting. The table was generated from a questionnaire developed by the first author and the responses from each respondent are incorporated in the table.

Table 3 Potential Benefits of DoE in Non-manufacturing/ Service Industries

Respondents and their affiliations	Benefits
Kai Yang, Wayne State University, USA	• To evaluate the cause-effect relationship between a set of service process variables and service performance characteristics
Phil Rowe, Consultant and Six Sigma Master Black Belt, Bourton Group, UK	• It promotes a scientific approach to understanding service business processes and customer behaviours – it changes a culture from gut feel to fact-based.

	• It reveals interactions which would never be understood otherwise
Mark Anderson, Stat-Ease, USA	• Reduce cost of quality due to rework and misinformation that led to bad decision-making
Larry Smith, Independent consultant, USA	• DoE provides a better understanding of cause-effect relationships between what we do and what we want to achieve, so that we can more efficiently optimize performance of the system we are working in.
Sung Park, Seoul University, South Korea	• Since service organizations also seek customer satisfaction, variation reduction, quality improvement and reduction of COPQ, DoE can provide a solution among many possible alternatives.
Ronald Snee, Consultant, Tunnell Consulting, USA	• Is systematic • Is efficient and low cost • Can estimate the effects of interactions • Can deal with excessive variation problems in service performance characteristics
Matthew Hu, Consultant and MBB, USA	• DoE is a good tool to help service organizations to quantify and understand the important process variables which causes variation so that the processes can be improved.
Alessandro Laureani, MBB, Hertz Services, Ireland	• To identify interactions between factors or process parameters in a service process which influence the service output(s)
Ronald Does, University of Amsterdam, The Netherlands	• DoE is a powerful tool also in service organizations to establish relationships between the CTQ and the most important influence factors.
Roger Hoerl, General Electric, USA	• Able to get better information, and clearer understandings of cause-and-effect relationships, and to do so cheaper and easier than any other method • There is the additional advantage in service that very few of your competitors will be using this approach, unlike the situation in manufacturing and engineering. So it is one way of getting clear competitive advantage.

Table 4 shows the real benefits of DoE in the context of non-manufacturing/service. The table is generated from a review of various case studies and examples from periodicals, textbooks, websites and white papers. The case studies represent a broader range of services from administration, customer service, financial services and healthcare settings.

Table 4 Real Benefits of DoE in Non-manufacturing / Service Processes

Area	Design	Benefits achieved
Bill Processing in a Utility Company	A one-way randomised ANOVA design with three experimental treatments was selected	• Reduction of 70% in the number of hours taken to process bills without incurring capital cost or increasing any human resource. • Savings generated from the project were estimated to be well over $100,000 US per annum • Better understanding and a greater insight into how process works
Direct Mail Response at Mother Jones Magazine	16 trial Fractional Factorial design was executed to study seven factors at 2 –levels	• Two factor interactions were studied to understand the effect of one factor on the response at different levels of the other factor • Better understanding of the process • The number of people who returned the reply card without payment decreased from 10% to 5%
Account receivables	8 trial Fractional Factorial design was performed to study 4 factors at 2-levels	• The receivables age can be reduced from the current average of 200 days to 44 days • Improvement in the cash flow in the company
Manpower Planning in Royal Navy	27 trial Full Factorial Experiment (simulation) was performed to study 3 risk variables within the manpower planning system	• Identified the optimal condition of risk variables which reduces the existing gapping at sea • 40% improvement over the current gapping at sea
Computer downtime in a small export company	18 trial Taguchi Orthogonal Array experiment was performed to study 8 factors at 3 levels.	• Improved the system response time by over 10% • Increased awareness of the use of more scientific approach to understand the system among many senior managers in the company
Response rate for a web retailer	16 trial Fractional Factorial experiment was carried out to study 5 factors at 2-levels.	• The response rate was improved by 75%
Billing process	Two level factorial experiment, studied over a dozen factors at 2-levels	• Savings of $2 million in postage • Developed a better telephone bill
IT services	A Full Factorial experiment was executed to study 3 factors at 2-levels	• The company did not have to replace and upgrade the existing server, thus avoid an expense of nearly $50,000
Hospital	12 trial Taguchi Orthogonal Array experiment was performed to study 11 factors at 2-levels	• Length of Stay (LOS) in Emergency Dept has been reduced from 100 minutes to 80 minutes • Cost savings was estimated to be well over $50,000
Financial Services	16 trial Fractional Factorial design was selected to study 5 factors at 2-levels	• Reduced rework rate due to incomplete information provided by the customer • Increased application completeness from 60% to 95% • Reduced cycle time for the loan and lease application process

Use of Computer Models

One of the difficulties in applying designed experiments in service and transactional businesses is that it is often difficult or impossible to physically experiment with the system under study. For example, suppose that we want to improve service operations in a hospital emergency department (ED). The response variable may be patient waiting time, and there may be several factors that could be considered as factors in a designed experiment, including varying the number of personnel on duty, the mix of skills in the on-duty personnel, the number of treatment rooms, the types of treatment and diagnostic equipment available, the physical layout of the ED, and the sequencing procedure that determines the order in which arriving patients are processed. Clearly some of these factors should have an effect on patient throughput and hence waiting times. However, varying these factors in a designed experiment would be impractical, and in most instances impossible. This situation is encountered in many improvement projects involving service and transactional operations. The Winter Simulation Conference held in December each year has a Health Care track that includes many instances of simulation models of Hospitals and health care systems. For examples of ED simulations that involve experimental design see Garcia et al. (1995), Miller et al. (2003), and Simon et al. (2003). Later in the paper, a case study is presented. The remainder of this section details the approach of experiments on computer simulation and some unique experimental design challenges.

The usual approach in these situations is to build a computer model of the process and then apply designed experiments to the model. If the model is

built properly and validated, then results from the experiment conducted on the model can be transferred to the actual process.

Broadly speaking, there are two types of computer models used in improvement activities, discrete-event simulation models, and deterministic models. Discrete-event simulation models are usually transaction-based and driven by random components that are modeled by probability distributions. For example, in the hospital emergency department application, the number of patients (or transactions) that arrive per hour may be modeled by a Poisson distribution whose mean is time-dependent, the type of complaint that the patient presents may be selected at random from a distribution that reflects the actual historical experience with patients, and the service time for each procedure that the patient undergoes could be modeled by an exponential or a gamma distribution (for example). Random numbers generated from these distributions move transactions through the system until either they are discharged or admitted to the hospital's general population. For an introduction to discrete-event simulation methods see Banks, Carson, Nelson, and Nicol (2005).

Because discrete event simulations are driven internally by random forces, they produce an output response that is a random variable. Consequently, the full range of standard experimental design methods, including factorial and fractional factorial designs and response surface designs can be applied to these models. Hunter and Naylor (1970) illustrate the uses of factorial, fractional factorial, and response surface designs in the context of two

computer simulation models and provide a brief discussion about the pitfalls associate with computer simulation experiments.

Some practical problems that arise when experimenting on computer simulations include sample size determination, the issue of multiple responses, and the problem of nonlinearity. Additional issues that are unique to computer simulation models, include how to choose the simulation run length and the duration of the warmup-period (if any is required). See Law (2007) for a discussion of these and other related issues. Also, if replication is used, it is usually standard practice to use a different stream of random numbers (or a different random number generator seed) for each replicate, so that replicates can be taken as blocks to reduce some of the variability in the model output.

Many discrete-event simulations have a large number of input variables. Depending on the simulation run length in real time there can be situations where the number of factors renders the use of conventional fractional factorial designs problematic. Supersaturated designs, which have fewer runs than the number of factors, can prove useful in these situations. Lin (2000) is a useful reference on construction of supersaturated designs. Forward stepwise regression can be used to analyze the data from a supersaturated design. See Holcomb, Montgomery and Carlyle (2003) for a discussion of other design construction and analysis methods. In some simulations there can be input variables that can be treated as noise variables. For example, in the hospital emergency department, the analyst may want to treat the patient

arrival rate as a noise factor because it cannot be controlled in practice by the management of the emergency department, and it may be desirable to try to find settings of the factors that can be controlled that work well across a wide range of arrival patterns. Designs that incorporate noise factors and methods for analyzing these designs to minimize the variability transmitted from the noise factors are discussed in Myers, Montgomery and Anderson-Cook (2009).

Simulation models can present other challenges for the experimental designer. Often the output response cannot be summarized by a singe summary statistic or group of summary statistics. Common situations are time series output, or functional output in which one response is related to one or more other responses through a functional relationship. In many case the output response may be poorly modeled by a normal distribution. For example in the hospital emergency room simulation the patient waiting times may follow a gamma distribution. Since the gamma distribution is a member of the exponential family, generalized linear models may be useful in the analysis of these types of responses. For examples of using generalized linear models to analyze data from designed experiments see Lewis, Montgomery and Myers (2001) and Myers, Montgomery, Vining and Robinson (2010). If the experimenter knows or suspects in advance that the response is an exponential family member, it is possible to design an experiment based on the D-optimality criterion that is more appropriate than classical designs. This is discussed in Johnson and Montgomery (2009) and Myers, Montgomery, Vining and Robinson (2010).

Design of Experiments: Case Examples from the Non-manufacturing Service Industry

Data entry errors

The Prescription Pricing Authority (PPA) is responsible for processing all prescriptions issued by medical doctors and dispensed by pharmacies throughout England. About 500 million prescriptions pa are processed by nearly 1000 staff. With a general rise in competition to supply such a service, there is a constant need to update and improve efficiency.

There are two main aims of the working process, to input data accurately and quickly. It had long been thought that asking staff to work as quickly as possible compromises accuracy levels; as input speeds become more rapid less care would be taken or fewer self-checks would be performed.

It was decided to run an experiment with two 3-level factors

- Staff factor: Experienced, Semi-Experienced and Novice
- Instructions factor: ‘go as fast as you can’, ‘be as accurate as possible’ and ‘go as fast as you can *and* be as accurate as possible’.

Thus, it would be discovered if particular instructions produced different effects in relation to different experience levels (Stewardson et al, 2002).

The trials proved a resounding success, with good co-operation being obtained from all staff. The experiment established that the speed of input

was the critical item that needed to be included in working instructions. Accuracy is affected by the experience level. If a person is asked to ‘go fast’, it will not tend to affect their accuracy level, however, if they are asked to be accurate, speed will reduce, without any noticeable effect on accuracy. It is thus favourable to insist on faster speeds and accuracy levels will, apparently, hold their ‘natural’ level. This is just one example of the use of a designed experiment involving human performance.

The key benefits of this designed experiment were that it showed the effect of issuing different types of commands on the speed and accuracy of data entry as well as evaluating the differences in performance between different types of staff. It also led to the establishment of a minimum expected performance standard for novices which helped determine recruitment and training needs. The experiment also allowed an assessment of the level of variation in data entry speed and accuracy between people.

Managerial implications were that a scientific approach could be applied to the assessment of performance. Statistical process control using cusum charts was also implemented for the data entry process and proved to be a workable methodology for deciding when bonuses should be given and when re-training was needed.

Lessons learnt included that a range of statistical techniques could be used in the context of the PPA which is effectively an enormous data processing plant. Many quality improvement initiatives were also carried out and random

sampling and statistical modelling were widely employed in a cross departmental acceptance of the importance of the quantitative approach. More recently extensive data mining has been undertaken to examine changes in the pattern of prescriptions over time as regards their value, content, source and mix with the aim of providing a foundation for process improvement.

Debt collection

Slow payment of invoices is a big problem and is particularly difficult for smaller companies. A continuous improvement project at a local SME looked at the performance of the whole flow of the company from receipt of orders to receipt of payment (Coleman et al, 2001).

In common with many companies, the manufacturing plant had been intensely modernised and was working very efficiently. Payment of invoices, however, was very slow and variable between customers. To help improve this situation, data were collected and analysed. It was found that the Pareto principle applied with most customers paying within reasonable time and some delaying unacceptably.

The ideas of experimental design were discussed at a problem solving team meeting. It was decided to see which factors would help speed up the payment of bills. It was noted from experience that it was better to phone after 2pm and to avoid phoning on Fridays. The aim was to try to find the optimum strategy and improve the time to payment of bills.

Three 2-level factors were chosen for the designed experiment:

- Written contact: send or do not send a letter
- Phone contact: phone or do not phone
- Timing of contact: 10 days after sending invoice or 30 days

Eight trials were planned. The debtor companies were randomly assigned to one of the eight trials. They were dealt with according to the experimental design and the time before payment was recorded. The outcome variable was the time to payment. It was found that sending a letter and telephoning 10 days after sending the invoice was by far the best strategy.

Applying this new strategy over the next few months, the time to wait for payment of bills was significantly reduced. Overall, the time from enquiry to payment was reduced from a mean of 110 days to a mean of 85 days. This reduction of 25 days is a significant improvement and could make the difference between staying in business and going out of business.

The key benefits of this exercise were introducing staff to the concept of logical problem solving. There were also major benefits from the team activity of setting up the experiment which involved identifying late payment as a problem, gathering information to quantify the problem, encouraging input from all the staff team, taking some action and showing a useful result. Even if the results are not particularly surprising, the designed experiment has the advantage of making it possible to quantify the effect of the new strategy so that the cost of writing and phoning can be justified. There are several

shortcomings in this experimental design, such as the skewed distribution of the measurable outcome, but, nevertheless it shows that experiments can be useful in a service context. In this SME designed experiments were used in the manufacturing plant and it was good for staff from all departments to share the methodology.

Managerial implications are that all staff can contribute to process improvement through quantitative analysis. The designed experiment provided more than just the measured outcome; an added bonus was that information was obtained as a result of the intervention and managers found out that many invoices were paid late because they were incorrect or had been lost in the post or had not been received for other reasons. The early intervention identified these problems so that they could be rectified.

Lessons learned are that it is possible to improve the payment of invoices. Recent contact with the company revealed that currently less than 1% of invoices are being paid late, which is a marked improvement.

Emergency Department Performance

Kolker (2008) describes a discrete event simulation model of the patient flow in a hospital emergency department. Three metrics, percent ambulance diversion, number of patients in the waiting room, and upper limit length of stay (LOS), were used to characterize the performance of the studied ED. A baseline simulation model, which represented the historical performance of the ED, was validated through the three performance metrics.

The author identified two main phases of the ED simulation study. The goal in the first phase was to utilize simulation and experimental design to create a response model that could be used to predict the metrics, such as percentage of ambulance diversion, as a function of the LOS for patients admitted as inpatients and LOS for patients admitted as outpatients (home patients). The goal in the second phase of the study was to determine an optimal ED closure criterion. ED closure would allow the ED to temporarily divert ED ambulance drivers to other hospitals in order to reduce the size of the queue in the waiting room. A factorial design was used to carry out the study in phase one.

Results of the experimentation performed on the simulation provided quantitative measures of the performance characteristics of the ED. Response surface modeling illustrated that the percent of ambulance diversions was negligible when LOS was less than 6 and 5 hours for inpatient and home patient visits, respectively. The ED closure criterion was when the number of patients in the queue was 11. Through the modeling of the ED department and use of historical data to drive the inputs, Kolker demonstrated how experimental design was beneficial in the context of analysis of the current system and the how to use findings of the study to influence management decisions.

Conclusion

Design of Experiments has been widely applied to quality and process related problems in manufacturing organisations. However research has indicated that very little attention has been given to the application of DoE in the context

of non-manufacturing or service processes. This paper attempts to demonstrate the power of DoE in a non-manufacturing /service environment. The benefits and challenges in the application of DoE in the context of non-manufacturing/service processes are presented and viewpoints from a number of practitioners and academics on the benefits and challenges are also highlighted. The paper also describes three simple case examples to illustrate the application of this powerful technique in non-manufacturing/service settings. The authors believe that DoE has tremendous potential but is greatly under-utilized in non-manufacturing/service organizations. We also expect to see more applications of DoE in non-manufacturing or service industries in the next 5 to 10 years or so because of the increased use of Six Sigma methodologies in the sector.

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