Effectiveness of the Design of Experiments (DoE) on Variation Reduction: Empirical Evidence for the Automotive Component-Manufacturing Sector in South Africa

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Abstract

In today's modern manufacturing environment, any process variability is an attack on quality and throughput. Variability reduction is paramount and necessary if higher levels of quality are to be obtained. Hence, this study evaluates the effectiveness of the Design of Experiments (DoE) as a strategic tool for reducing variation in the automotive component manufacturers in South Africa.

As with the evolution of the manufacturing process, methods to identify and eliminate process variability are developed. Most of these methods are based on statistical DoE. A DoE is a test or series of tests that enables the experimenter optimise the yield of a process or minimise variability. Consequently, this study focuses on the effectiveness of DoE for variability reduction in the automotive sector in South Africa. Of the 193 individuals identified for participation, 164 completed the questionnaires. Middle-level Managers from four automotive component-manufacturing companies in the eThekwini District Municipality participated in the study. The study investigated production and the related experiences of the automotive component manufacturing companies that have adopted a DoE strategy. Descriptive and correlation were used to analyse data.

The results indicates that DoE reduces product variation in the automotive component manufacturers in South Africa. In order to maximise performance, a comprehensive variability reduction policy must be developed, which aligns DoE tools to business performance. DoE has the ability to screen a large number of variables to find important ones during product reformulation process in the Product and Development functional areas.

Keywords: *automotive component manufacturers; design of experiment; functional areas of business; variation reduction.*

1. Introduction

DoE is a test or series of tests that enables the experimenter to compare two or more methods (Evans and Lindsay, 2011). It determines the better or controllable factors in order to optimise the yield of a process or minimise the variability of a response variable. This type of technique was first used by Fisher at the start of the twentieth century, but its application in the quality field has been most commonly associated with Taguchi (Johnson, Hutto, Simpson and Montgomery, 2012). It was Taguchi's application to industrial processes and products that gained the technique international acclaim. The technique, with the use of statistically designed experiments, enables an understanding of the effect, and can quantify the significance of a variable factor (parameter), and its contribution to changes in output (Sinha, 2011). Correctly implemented, it can optimise the process or product under investigation by exploiting the non-linear effects of the process parameters on the performance characteristics in order to determine settings that minimise variation within that product or process (Johnson *et al*., 2012). Common variation within a process is known as noise. It can occur as a result of ageing machinery and parts, inconsistent operating conditions ranging from atmosphere to operator skill, and fluctuation within predetermined settings (Simms and Garvin, 2002). Optimising the process involves determining the signal and control factors in the process and selecting the optimal parameter settings that are least sensitive to this noise. Signal factors are those that affect only the level of output, and control factors are those which affect the variation in output. If both are optimised the result is a robust process with reduced non-conformance and variability.

The reduction in non-conformance and variability is based on the assumption that if a process performs well in adverse conditions (as a result of noise factors) it will perform considerably better in normal conditions (Aboelmaged, 2010). Hence, this study examines the effectiveness of DoE as a management tool in reducing variation. It determines the ability of DoE in improving processes in various functional areas of business. The study is guided by the following research questions (RQs):

- RQ1: Is DoE capable of reducing product and process variation in the automotive component manufacturers in South Africa?
- RQ2: Does DoE influences product improvement through reformulation during product development?
- RQ3: Is DoE has the ability to reduce variation in various functional business areas?

The rest of the study discusses literature review, methodology used, study results, discussion, implication of results for policy and practice, study limitations, conclusion and future research required.

2. Theoretical Consideration

This section discusses the overview of DoE as a management tool that reduces variation. It elaborates on the management approach for DoE success.

2.1. Brief overview of DoE as a management tool that reduces variation

This section commences by defining a DoE. Its approach as a statistical tool that reduces variation is explained.

The DoE is a statistical technique that has been adopted to perform experimental studies focused in product and process improvement (Sinha, 2011). DoE differs from observational statistical studies in that the factors of interest are controlled by the experimenter, rather than simply observed through the selection of randomised samples (Evans and Lindsay, 2011). Although many authors are enthusiastic about the use of DoE (Johnson *et al*., 2012), there is a wide gap between theoretical development and its effective application in industry (Sinha, 2011). The difficulties faced by users of statistical tools are often neglected and have caused some reluctance in their implementation. Moreover, the practical results obtained with DoE are sometimes far from what would be expected. According to Pepper and Spedding (2010), the knowledge and employment of DoE is not significant even in larger and developed companies. Nuno, António and Celma (2006) in Aboelmaged (2010) indicate that DoE is not an easy technique to be applied due to limitations in technical knowledge of the product and technologies involved. Salah, Rahim and Carretero (2010) indicate that an inadequate training in basic statistical concepts and methods by the engineers and other process specialists, as well as the lack of computing and software resources to support the application of statistically designed experiments are some of the limitations.

As pointed out by Park, Ntuen and Park (2009), statistical models can rarely transform poor engineering knowledge into useful information. However, Ghosh and Maiti (2014) state that practitioners cannot become experts in statistics and select the appropriate techniques to use. In their opinion, it is necessary to develop statistical methods into easily understood strategies for solving specific problems.

Some methodologies and approaches to guide the experimental process emphasising technical issues on the use of statistical techniques, namely DoE, have been presented in historical literatures (Anderson-Cook, Patterson and Hoerl (2005); Montgomery, 1992; Antony, 1999; Taguchi, Chowdhury, and Wu, 2005). Successfully implementations of statistical techniques in industry are also presented in many papers. Rarely published and discussed are unsuccessful experiments in which the expected information was not obtained for a variety of reasons that are not evaluated (Salah, Rahim and Carretero, 2010). On the same note, Sinha (2011) indicates that there are difficulties in experimental studies, particularly, in the application of DoE. Whilst a large number of companies are not successful in the application of DoE (Salah *et al*., 2010), the majority of such studies are omitted. Lack of management commitment and training, as well as inadequacy in employing statistical techniques are usually pointed out as the main reasons of failure (Heavey and Murphy, 2012). On the other hand, Tanco, Viles, llzarbe and A'lvarez (2009), alluded to the fact that managers are unaware of the importance of statistical techniques in processes and products development. Although it is impossible to assure that statistical techniques will permit the attainment of the defined objective, it is important to reinforce the idea that non-statistical aspects in planning and conducting experiments are as important as the formal design and analysis (Vinodh, Kumar, and Vimal (2014). However, this study examines the effectiveness of DoE as a management tool to reduce variation in the automotive component manufacturing companies in South Africa.

2.2. Management approach for DoE success

Experimental studies may fail not only as a result of lack of technical knowledge or wrong use of statistical techniques, but also due to lack of planning (Vinodh *et al*., 2014). To overcome this gap, considering the experiences in planning experimental programmes and what hinders or helps the process of effective application of experimental designs, Ghosh and Maiti (2014) explain that it is necessary to pay special attention to the following organisational and technical management aspects. Consequently, this study examines the effectiveness of DoE in improving processes in various functional areas of business.

2.2.1. Organisational management aspects:

Staff responsibility. It is top management responsibility, through attitudes and leadership, to create an environment that stimulates a culture of continual improvement and change (Vinodh *et al*., 2014). Staff motivation and commitment are critical to the success of statistical techniques implementation on products and processes development. Careful allocation of material and human resources based on cost-benefits analysis, and training human resources in statistical techniques necessary to improve product and process must be continuous if the improvement effort is to be sustainable. An adequate training programme should help employees discover innovative ways to improve the organisation and shoulder the responsibility for effecting improvements (Aboelmaged, 2010).

Team approach. Modern management practices usually make use of multidisciplinary teams to collect and analyse specific subjects. For instance, in the biomedical and pharmaceutical industry, multidisciplinary research teams typically work closely together (Bisgaard, 2008). Even employing statistical methods, the process and product complexity imposes formal creation of multidisciplinary teams to share experiences and specific technical knowledge to get improvements. Statistical methods, like experimental design techniques, works only in conjunction with scientific knowledge, not as a substitute. The multidisciplinary team should include a formal supervisor with responsibilities and authority defined by top management, who should be an effective communicator with good interpersonal skills and awareness of group dynamics. The team also needs someone well trained in statistical techniques and people from different hierarchical levels and activities depending on the problem to be analysed. Sharing experiences and individual knowledge is critical to assure a deeper understanding about the process and the product, providing more efficient ways to design experiments and to attain the study objective.

Opportunities identification. To support continual improvement, the identification of opportunities should be a systematic activity that results from a culture background encouraging innovation and people participation (Vinodh *et al*., 2014). It requires research and knowledge, which can be efficiently achieved through team approach and adequate tools. Brainstorming, benchmarking and technical literature may be ways to identify opportunities.

2.2.2. Technical aspects:

Measurements. Special attention should be paid to gathering data. Defining a measurement system, including human resources, equipment and measurement methods, is a fundamental aspect in planning experimental studies (Aboelmaged, 2010). Actions to be taken include the definition of a responsible person for performing the experiments, the identification of infrastructure and equipment that should be used and how to use it. Besides, it is important to assure that equipment exists, is suitable, accessible and calibrated. Procedures defining how to use it may be useful. The quality of a measurement system is usually determined by the statistical properties of the data it produces over time (Sinha, 2011). Although statistical properties of the measurement system may change as the items being measured vary, there are fundamental properties that define a "good" measurement system (Vinodh *et al*., 2014).

Documentation. Mistakes in experimental procedures affect the validity of results and the success of research (Sinha, 2011). Detailed documentation and rigorous definition of previous and following tasks are essential and particularly appropriate for complex experimental studies. Fundamentally, it is necessary to identify clearly what has to be done, why it has to be done, the way it must be done, when it must be done and who is going to be involved in the practical part of experimentation. All documentation, including data collection forms, must be easy to use, understandable and avoid misinterpretations.

3. Methodology

The method used in this research will be discussed under the following headings, namely: research design and approach, the target population, sample size, data collection as well as the measurement and analysis.

3.1. Research design and approach

This study was quantitative in nature. Bryman and Bell (2007) explain that the quantitative approach involves the use of statistical procedures to analyse the data collected. Consequently, after the measurements of the relevant variables, the scores were transformed using statistical methods. The study was also conclusive in design. Conclusive studies are meant to provide information that is useful in reaching decision making (Yin, 2008).

3.2. Target population

Four automotive component manufacturers in the eThekwini District Municipality participated in the study. The target population comprised of 193 Middle Managers. These individuals were either operating from production or administrative sections of the companies.

3.3. Sample size

A simple random sampling technique was used to select the participants. A sample size of 164 Middle Managers participated in the study. This comprised of 105 Middle Managers from production and 59 from administration.

3.4. Data collection

The collection of data was achieved by physically distributing the questionnaires to the Human Resource departments of participating companies. Similarly, the completed questionnaires were returned to the researcher via the Human Resources departments of the four participating companies. One-hundred-and-seven questionnaires were returned, representing an 85 per cent response rate, considered high compared with the norm for survey responses (Baruch and Holtom, 2008). The main reason for this high response rate was due to the invitation letter sent to the participants and consistently following up the questionnaires through telephone calls.

3.5. Measurement and analysis

In line with research framework, the study measured 15 variables using the questionnaire. It employed a Likert scale, ranging from 1 (strongly agree) to 5 (strongly disagree). Descriptive and correlation analysis were used to test the two objectives.

- ***The influence of DoE as a management tool that reduces variation:*** Four items are listed as the influence of DoE as a tool to reduce variation. These include DoE as a tool that: eliminates confounding effects where the effects of design variables are mixed up; determines the important variables that need to be controlled; determines the unimportant variables that may not need to be controlled; and measures interactions.
- ***The ability of DoE in improving processes in various functional areas of business:*** The following variables measured the ability of DoE in the various functional areas of the automotive business. These include:
  - **Research:** to screen a large number of variables to find important ones;
  - **Product development:** to develop new products;
  - **Quality control:** to set specifications on quality characteristics;
  - **Purchasing:** to establish product specifications;
  - **Engineering:** to find optimum machine operating parameters.

The Statistical Package for the Social Sciences (SPSS) version 23.0 was used to analyse data.

4. Study Results

4.1. The impact of DoE as a management tool that reduces product variation

The following Table 1 presents the impact of DoE as a management tool that reduces product variation. It provides responses for both the administrative and production Middle Managers.

Variables	Middle Managers' responses (in percentages) accepting this perception
To eliminate confounding effects whereby the effects of design variables are mixed up	71
It determines the important variables that need to be controlled	98
It determines the unimportant variables that may not need to be controlled	82
It measures interaction	84

Table 1. Impact of DoE as a management tool that reduces product variation
Source: data from research survey

Middle Managers in Table 1 agreed that DoE has an impact on reducing product variation. Critical factors on its ability to determine the important variables that needs to be controlled is at 98 per cent, measures interactions at 84 per cent and determines the unimportant variables that may not need to be controlled at 82 per cent. However, the elimination of confounding effects, whereby the effects of design variables are mixed up, had a low response at 71 per cent.

In addition, the correlation analysis was used to test the two objectives. That is, the influence of DoE as a management tool that reduces variation, as well as the influence of DoE as a management tool in various functional business areas.

4.2. The influence of DoE as a management tool that reduces variation

The Pearson correlation tests were used to find any significant relationship between study variables, where any two-study variables are dependent or independent of each other, and to find the direction and strength of dependency (Cooper & Emory, 1995). Correlation can reveal the significance of correlation; if significant, whether it is positive or negative (direction of correlation) as well as the strength of the correlation.

The tests for significant relationships between the variables for the influence of DoE as a management tool in Table 2, with the product and process performance, were done on both sub-sections 4.2.1 and 4.2.2. The two performance variables include: product improvement through reformulation in Product Development and process optimisation through quality control tools. These two variables are tested with DoE study variables:

- to eliminate confounding effects where the effects of design variables are mixed up;
- to determine the important variables that need to be controlled;
- to determine the unimportant variables that may not need to be controlled;
- and to measure interactions.

Variables		Product improvement through reformulation in Product Development	Process optimisation using quality control tools such as Statistical Process Control (SPC)
To eliminate confounding effects where the effects of design variables are mixed up	Correlation	0.264**	-0.164
	Sig. (2-tailed)	0.006	0.091
	N	164	164
To determine the important variables that need to be controlled	Correlation	0.083	0.052
	Sig. (2-tailed)	0.398	0.592
	N	164	164
To determine the unimportant variables that may not need to be controlled	Correlation	0.084	-0.147
	Sig. (2-tailed)	0.389	0.130
	N	164	164
To measure interactions	Correlation	0.078	-0.105
	Sig. (2-tailed)	0.422	0.282
	N	164	164

**Correlation is significant at the 0.05 level (2-tailed)*

Table 2. Influence of DoE as a management tool that reduces variation
Source: research data, 2018

4.2.1. The influence of DoE and product improvement through reformulation in Product Development

The following DoE variables in Table 2 do not statistically have a significant relationship with product improvement through reformulation in Product Development. These include DoE variables to:

- determine the important variables that need to be controlled [r(164=0.083, p>0.05)];
- determine the unimportant variables that may not need to be controlled [r(164=0.084, p>0.05)]; and
- measure interactions [r(164)=0.078, p>0.05)].

However, the variables of DoE that ensure that it eliminates confounding effects where the effects of design variables are mixed up and the variable for product improvement through reformulation during the product development, have a coefficient r-value of 0.264 (at p<0.05). This is a directly proportional and medium correlation between the two variables. Respondents believe that, as the DoE becomes influential in reducing variation, products improve during the process of reformulation (that is, alteration or revision).

4.2.2. The influence of DoE and process optimisation using quality control tools

The following DoE variables in Table 2 do not statistically have a significant relationship with process optimisation using quality control tools such as Statistical Process Control. These include DoE variables to:

- eliminate confounding effects where the effects of design variables are mixed up [r(164)= -0.164, p>0.05)];
- determine the important variables that need to be controlled [r(164)= -0.053, p>0.05)];
- determine the unimportant variables that may not need to be controlled [(r(164)= -0.147, p>0.05)]; and
- measure interactions [r(164)= -0.105, p>0.05)].

4.3. The ability of DoE to reduce variation in various functional business areas

The Pearson correlation tests were used to find any significant relationship between study variables, where any two-study variables are dependent or independent of each other, and to find the direction and strength of dependency. The tests for significant relationships between the variables for the influence of DoE as a management tool that reduces variation on Table 3 with the product and process performance were done on both sub-sections 4.3.1 and 4.3.2. The two performance variables include: product improvement through reformulation during product development and process optimisation through quality control tools. These two performance variables are tested with the study variables. Consequently, the study variables are categorised in accordance to various functional business areas. These include:

- **Research:** screens a large number of variables to find important ones;
- **Product Development:** develops new products;
- **Quality Control:** sets specifications on quality characteristics;
- **Purchasing:** establishes product specifications;
- **Engineering:** finds optimum machine operating parameters.

4.3.1. Ability of DoE on product improvement through reformulation during product development

The following influences of DoE variables in Table 3 do not statistically have a significant relationship with product improvement through reformulation. They include the following DoE variables:

- **Quality Control:** to set specification on quality characteristics [r(164)=0.185, p>0.05)];
- **Purchasing:** to establish product specifications [r(164)=0.173, p>0.05)];
- **Engineering:** to find optimum machine operating parameters [r(164)= -0.091, p>0.05)].

However, the ability of DoE that ensures that it screens a large number of variables to find important ones (in the Research functional area) with a coefficient r-value of 0.336 (at p<0.05), and has the ability to develop new products (during product development functional area) with a coefficient r-value 0.430 (at p<0.05), has a directly proportional and medium correlation between them. Respondents believe that, as the ability of personnel to use DoE tools becomes stronger, companies are able to screen a large number of variables to find important ones, and develop new products.

Variables in functional business areas			Product improvement through reformulation during product development	Process optimisation using quality control tools such as SPC
Research	Screens a large number of variables to find important o nes	Correlation	0.336**	-0.039
		Sig. (2-tailed)	0.000	0.691
		N	164	164
Product Development	Develops new products	Correlation	0.430**	0.206*
		Sig. (2-tailed)	0.000	0.033
		N	164	164
Quality Control	Sets specifications on quality characteristics	Correlation	0.185	0.581**
		Sig. (2-tailed)	0.057	0.000
		N	164	164
Purchasing	Establishes product specifications	Correlation	0.173	-0.055
		Sig. (2-tailed)	0.074	0.574
		N	164	164
Engineering	Finds optimum machine operating parameters	Correlation	-0.091	0.544**
		Sig. (2-tailed)	0.354	0.000
		N	164	164

Correlation is significant at the 0.05 level (2-tailed)

Table 3. Ability of DoE to reduces variation in various functional areas of business
Source: research data, 2018

4.3.2. The ability of DoE on process optimisation using quality control tools

The following DoE variables in Table 3 do not statistically have a significant relationship with process optimisation using quality control tools such as SPC. They include the following DoE variables:

- **Research:** to screen a large number of variables to find important ones [r(164)= -0.039, p>0.05)];
- **Purchasing:** to establish product specifications [r(164)= -0.055, p>0.05)].

However, the ability of DoE ensures that: it develops new products (in the Product Development functional area) with a coefficient r-value of 0.206 (at p<0.05), it sets specification on quality characteristics (in the Quality Control functional area) with a coefficient r-value of 0.581 (at p<0.05), and it finds optimum machine operating parameters with a coefficient r-value of 0.544 (at p<0.05). These are directly proportional and medium correlations between the three variables. Respondents believe that, as the ability of personnel to use DoE tools becomes stronger, companies are able to develop new products, set specification on quality characteristics, and find optimum machine operating parameters.

5. Discussions

The study examined the production and related experiences of four automotive component-manufacturing companies that have adopted a DoE strategy. The four companies operate in the eThekwini District Municipality in KwaZulu-Natal in South Africa. Consequently, this study assesses the effectiveness of DoE as a management tool for the reduction of variation. It assesses the ability of DoE in improving processes in various functional areas of business. The results indicate that DoE has an impact in reducing product variation. This is shown by a huge percentage response agreeing with the influence of DoE on variation reduction. For the success of DoE, Aboelmaged (2010) advised that there should be an adequate training programme that helps employees discover innovative ways to improve the organisation and shoulder the responsibility for improvements. It has also been established that DoE eliminates confounding effects where the effects of design variables are mixed up. Its techniques have the ability to screen a large number of variables to find important ones (in the Research functional area) and develop new products (in the Product Development functional area). This is supported by Vinodh *et al*. (2014) who insists that DoE requires research and knowledge that can be efficiently achieved through team approach and adequate tools. Brainstorming, benchmarking and technical literature may be ways to identify opportunities.

6. Implications of Results for Policy and Practice

DoE methods have achieved considerable success in many industries (Evans and Lindsay, 2011). This research has established that DoE has the capability to reduce variation in automotive component manufacturing companies in SA. Besides the achievement of the study objective, the following conclusions can be made. DoE has the ability to:

1) eliminate confounding effects where the effects of design variables are mixed up; and
2) screen a large number of variables to find important ones during product reformulation processes in the Product and Development functional area.

7. Study Limitations

The study was limited to the automotive component manufacturing industry within the eThekwini District Municipality. The investigation was conducted in four companies that have adopted DoE. Hence, the result cannot be generalised to other companies operating in other sectors of the economy.

8. Conclusion

In order to maximise performance, a comprehensive variability reduction policy must be developed, which aligns DoE tools to business performance. DoE creates a working environment that encourages worker participation and provides opportunity for improving business performance through the reduction of variation in both the products and processes (Vinodh *et al*., 2014). It is a system that can be used to screen a large number of variables and eliminate their confounding effects where the effects of design variables are mixed up (Sinha, 2011).

9. Future Research Required

The nature of this study did not allow the investigation to determine the long-term DoE survival to a wider sector of the economic activity. It is recommended that a future study should examine the following issues in greater depth:

- when to use and when not to use a DoE system; and
- the applicability of DoE to other industrial sectors.

The study investigated the effectiveness of DoE as a management tool for the reduction of variation. It examined the ability of DoE in improving both the products and processes in various functional areas of business. The results indicate that DoE has an influence in reducing product and process variation. It has the ability to screen a large number of variables to find important ones during product reformulation process in the Product and Development functional areas.

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