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Using a Parameter Diagram as a DoE Planning Tool

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Abstract
This paper describes the p-diagram (parameter-diagram) and its application in planning a DoE (Design of Experiments). A case study describing an actual problem from industry is presented where the planning phase started to go wrong as difficulties in selecting the right variables for the DoE were discovered. Furthermore, running these experiments became prohibitively expensive, due to the large number of such experiments that would be needed, and though the exploitation of a p-diagram it was then possible to come up with a feasible DoE.

Keywords
Design of Experiments; Parameter-Diagram; p-Diagram; DoE; Experiment Planning.

Introduction

The origins of DoE (Design of Experiments) date back to R.A. Fisher who developed the methodology to analyze agricultural experiments (Gunter, 1989). There are many reasons for performing a DoE, such as improving a process yield, reducing process variability, reducing development time, or lowering operating costs (Borror, 2009). The main objective of a DoE is often to determine the main sources of variability, or to increase or decrease a certain value (Benbow & Kubiak, 2009). In the case study presented in this paper, the objective was to understand the effects of potential quality problems on the performance of a system under test conditions that simulated real world usage.

There is specific terminology used for DoEs. For example, factors are "variables that are studied at different levels in a designed experiment" (Breyfogle, 2008) and a level "is the setting or assignment of a factor at a specific value" (Benbow & Kubiak, 2009). The response or response variable is "a characteristic of the experimental unit which is measured during and/or after each run" (Lawson & Erjavec, 2001) as the main desired output. Each experimental trial in a DoE is called a run (Montgomery et al., 2001). The number of required runs in a DoE may be too expensive or time consuming to actually perform with every possible combination; in such situations, a fractional factorial DoE can be performed where not every possible combination is tested (Vining & Kowalski, 2006).

Each run during a DoE has the factors set to different levels and the result of the run gives the experimenter the corresponding values for the response variable.

Proper planning is required before executing a DoE or resources such as time and money could be wasted, or even worse, the experimenter may reach the wrong conclusions without being aware that there is a problem. Vandenbrande (2005) warns that although things can go wrong at any point in a DoE, the worst damage is done when something goes wrong before the experiment is even started because an incorrectly set up experiment can't be saved.

When planning a DoE, Anderson & McLean (1974) recommend recognizing the existence of a problem, describing the problem, and determining factors and levels which will be used. Montgomery et al. (2001) recommends recognizing the existence of the problem and describing it, choosing the factors and levels as well as the ranges, identifying a response variable, choosing the type of design, performing the experiment, analyzing the data statistically, reaching conclusions, and providing recommendations.

The first steps in DoE planning are recognition of the existence of a problem that could be solved through the use of a DoE and clearly understanding what should be accomplished by the DoE. Without an understanding of the objectives, the wrong factors

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or response variable may be inadvertently selected. An example of a problem statement for a DoE is "The overall process yield for the back-door glass was 90.2% from April 2013 to February 2014 against the budgeted target of 93.5%" (Kuma et al., 2016); here, the problem was a lack of glass of sufficient quality to meet customer demand.

Freeman et al. (2013) describe a seven step approach to DoE with the first steps related to DoE planning. First the problem is defined and then the response variable is selected. Sources of variation are then identified and used to select the factors and levels as well as blocks. The experimental design is then selected, the experiment is performed, and the data is analyzed. Finally, conclusions and recommendations are drawn from the experiment.

This paper studies the use of a p-diagram in the planning of a DoE. A p-diagram is not a new tool and it is often used in the automotive industry for the creation of a Design Failure Modes and Effects Analysis (DFMEA). The use of a p-diagram as a DoE preparation tool, however, is a new application of the concept. A p-diagram considers both the inputs and outputs of a system (Brue & Launsby, 2003) and depicts them graphically. More specifically, a p-diagram "is a structured tool to help the team understand the physics related to the function(s) of the design" (Chrysler, Ford, General Motors Supplier Quality Requirements Task Force, 2008). The concept of a p-diagram is depicted in Figure 1.

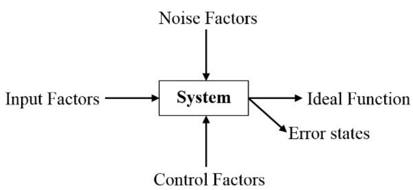

Fig. 1. p-diagram

The inputs may be the main inputs for a product such as raw material or a control signal in the form of voltage. There are also noise factors. Noise factors also influence a system, but these are uncontrolled, such as weather or wear over time. Noise factors include the variation between parts, interactions with other components, the way in which customers use a product, environmental influences, and degradation over time (Yang & El-Haik, 2009). Also included in a p-diagram are control factors and error states (Barsalou, 2015); control factors are directly controlled, such as when they are tested beforehand to ensure they conform to requirements or design decisions that impact the product and error states are the ways in which things can go wrong.

Literature review

The use of Ishikawa diagrams in planning a DoE has been recommended in the literature (Breyfogle, 2003) and illustrated in a case study (Ophir et al., 1988); however, the use of a p-diagram tool is a new concept and as such it is not documented in the literature, so details of four published DoEs were retroactively converted into p-diagrams to illustrate the use of this method. These DoEs were a battery study to determine the optimal AA battery for an intended usage (Waisiloff & Hargitt, 1999), improvement of a molded medical device (Azeredo et al., 2003), increasing the lifetime of a molded tank deterrent device (Yadav, 2007), and the improvement of a silver powder production process (Johnson & McNeilly, 2011).

Wasiloff and Hargitt (1999) performed a DoE to identify the optimal type of AA dry-cell battery to use for remote control model race cars. The factors were cost (with levels high cost and low cost), connectors (with levels standard and cold plated), and battery temperature (with the levels ambient and cold). Figure 2 shows a p-diagram which has been created based on the information provided in the article.

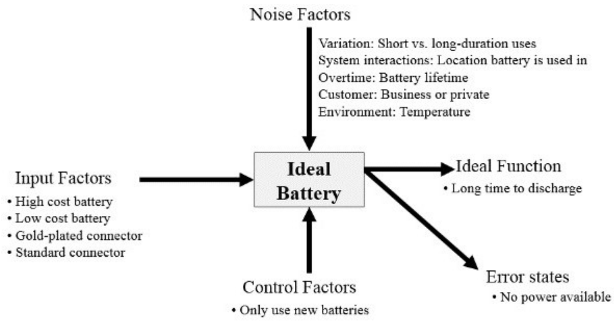

Fig. 2. p-diagram for AA battery selection based on Wasiloff & Hargitt (1999)

In the next example, Azeredo et al. (2003) performed a DoE to optimize the opening force of an injection molded plastic medical device. Here, the factors were injection speed as a percentage of setting, mold temperature, melt temperature, holding pressure in bar, holding time, cooling time, and ejection speed as a percentage of setting. A p-diagram based on this DoE is depicted in Figure 3.

An injection molded part used for filling explosives devises as part of a tank deterrent was required to last ten years under environmental conditions, so a DoE was performed to increase its lifetime. The survival time in an environmental stress crack test was the response variable with a target value of being above

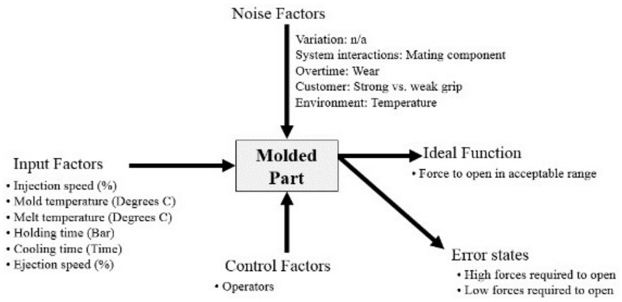

Fig. 3. p-diagram for a molded medical device based on Azeredo et al. (2003)

ten hours. The factors in Figure 4 are temperature in the barrel on the molding machine, refiling time, method of cooling, cycle time, injection pressure, injection time, and hold time with more or less used as levels (Yadav, 2007).

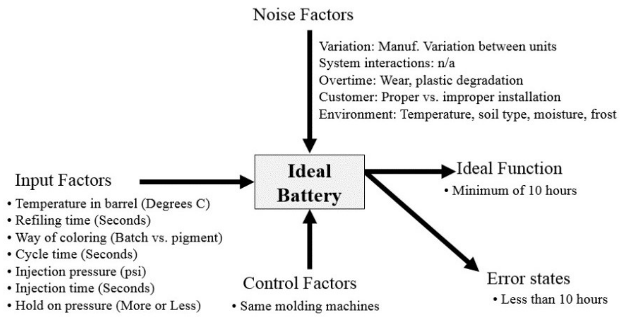

Fig. 4. p-diagram for improved lifetime of a molded tank deterrent device based on Yadav (2007)

The final example is based on the improvement of a silver powder production process where there were two response variables; surface area within a range and density, which needed to be below 14 grams per cubic centimeter. The input factors which were used as the DoE factors were percent ammonium, the stir rate, and temperature (Johnson & McNeilly, 2011) as shown in Figure 5.

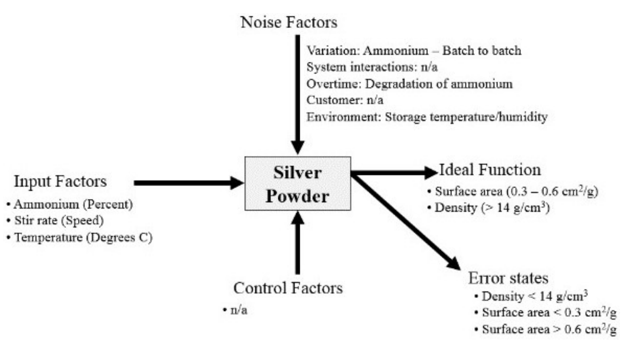

Fig. 5. p-diagram for a silver powder production process improvement based on Johnson and McNeilly (2011)

Case study

This paper uses a descriptive case study methodology. Case studies are a form of research which have the advantage of exploring deeper into events that the research cannot control. Typically, data for a case study is gathered through reviewing documents, conducting interviews, and direct observation (Verleye, 2019). In this case study, a researcher conducted interviews and reviewed relevant documents.

The details in this case study have been changed to obscure the identity of the organization involved. Specifically, the component names have been changed and all values have been changed by multiplying them using the same multiplier.

A quality engineer in a large manufacturing organization was planning a DoE to determine the impact of various potential quality problems on the performance of a product. A problem statement existed. However, she was uncertain about how to proceed, so she consulted with a Lean Six Sigma Master Black Belt. There were three product sizes, and side A had four potential failures to consider and side B had three potential failures. The components and failures are shown in Table 1 with failure types coded as letters.

Table 1
Potential factors and levels

Factor	Level 1	Level 2	Level 3	Level 4
Small side A	A	B	C	D
Small side B	X	Y	Z	n/a
Medium side A	A	B	C	D
Medium side B	X	Y	Z	n/a
Large side A	A	B	C	D
Large side B	X	Y	Z	n/a

A full factorial DoE for all combinations would require 512 runs without replication and this would be too expensive to actually be performed. It was quickly determined that many of the combinations were unrealistic; different sizes would never actually be together in one assembly. Furthermore, each possible failure could have a range of values, so the DoE would not yield the necessary information if it was not properly planned.

Finally, each test would on average cost approximately 5 000 Euro in addition to the cost of procuring special parts for testing. The cost for a full factorial DoE would be not less than 2 560 000 Euro. With replication, costs would exceed 7 680 000 Euro for a full factorial DoE.

The planning session was then paused and a worksheet was created to help facilitate this DoE planning. Planning would continue only once the problem was well understood and the system's inputs and outputs were well identified.

Better planning was required, so it was decided that all initial critical information should be available in one document that could be consulted while planning the DoE. The worksheet shown in Figure 6 was created to serve as a DoE planning tool. The worksheet's first requirement was the identification of the person holding overall responsibility for the DoE. A field was also added for the current date to ensure the latest version is always used. The next field is for the identification of the team members; a DoE should not be planned by just one person and experts from various fields must often be consulted.

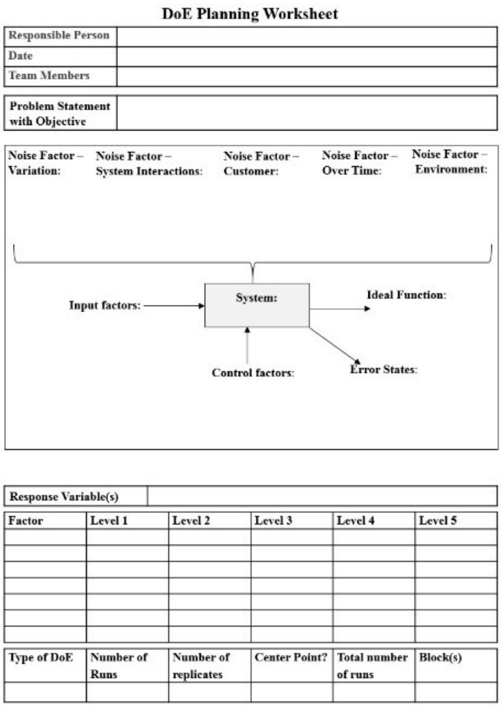

Fig. 6. DoE planning worksheet

A field was made available for the problem description with the overall objective; this was to ensure the problem description was available for reference during future planning meetings. It is important for the team members and consulted experts to understand what is being investigated and what the intended objective is.

This document was created in a presentation program to make it easier to update the field containing a p-diagram, which was to be used to gain a better understanding of the overall system, prior to attempting to determine what type of DoE should be performed.

Potential DoE factors can be drawn from the input and control factors, while noise factors can be useful for identifying potential blocks. The types of noise factor are part to part variation, system interactions when the system is installed together with other components or assemblies, customer usage changes over time, and environmental influences. These noise factors might not all be relevant to a specific DoE such as when an assembly is not tested together with other parts; however, the five types of noise should still be included in the document to serve as a checklist to help ensure they are at least considered.

The response variable would either be the ideal function, when it must be optimized, or the error state when there is a condition that should be avoided. The p-diagram could be created in a presentation program as was done here or even drawn a whiteboard with a photograph inserted into the planning document. However, regardless of what medium is used to create a p-diagram, SMEs (Subject Matter experts) are needed to provide the right p-diagram inputs. Their inputs are needed for a proper DoE and use of the p-diagram helps to ensure they are captured during DoE planning.

The DoE team would then use the p-diagram to assist in planning the DoE. The document also contains fields to list the response variable, factors, and the levels of the factors. This information would then be used to identify the type of DoE required and the resulting number of runs, replicates, center points if necessary, and the total number of runs. There is also a field for listing any blocks if blocking is necessary.

The DoE planning form was then completed, and the top of the form is shown in Figure 7 with the names changed to ensure anonymity. A team leader was assigned overall responsibility for the DoE and a champion was identified for supporting the team leader in regards to budget and organizational obstacles. Team members from various departments were then selected based on expertise.

Responsible Person	Team Leader – Lisa Sander (Quality Engineer)
Date	05 October 2019
Team Members	Delores Lynch (Statistical support), Johnathan Hammond (Product Engineer), Phyllis Marsh (Testing System Engineer), Champion - Stephen Gibbs (Development manager)
Problem Statement with Objective	Perform a DoE to identify the influence of quality deviations of critical characteristics effecting product performance as indicated by test system results

Fig. 7. Top of the completed DoE planning form

A p-diagram was created by the team (Figure 8). The response variables of interest were determined to be output volume and efficiency at each side. Although there were four response variables, this would not change the number of runs required as data for all four would be collected during each run. They only needed to be analyzed separately. Each size class needed to be a separate DoE and the factors were determined to be R/S body entrance diameter, R/S body entrance diameter surface roughness, R/S body distance flange to ridge as percent of diameter, L/S body exit diameter, and L/S body exit diameter surface roughness. The number of required runs was still going to be high, so the team decided to check to ensure all of the failure types do actually happen. A database of failures showed that one had never occurred, so the theoretical failure was removed from consideration.

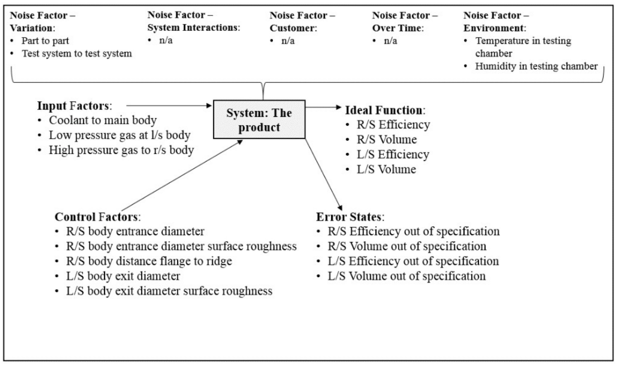

Fig. 8. p-diagram used for DoE planning

Figure 9 shows the factors and levels for a general full factorial DoE. This DoE would require a total of 324 runs, which is much less than the originally anticipated number of runs, but would still be prohibitively expensive, due to a cost of around 1 620 000 Euro. The champion would be unlikely to approve such a massive financial expenditure.

Response Variable(s)			R/S Efficiency , R/S Volume, L/S Efficiency, and L/S Volume			
Factor			Level 1	Level 2	Level 3	Level 4
R/S body entrance diameter			14	19	24	Not applicable
R/S body entrance diameter surface roughness			70	Not applicable	140	Not applicable
R/S body distance flange to ridge as percent of diameter			4	7	10	Not applicable
L/S body exit diameter			18	22	26	Not applicable
L/S body exit diameter surface roughness			70	Not applicable	140	Not applicable
Type of DoE	Resolution Type	Number of Runs	Number of replicates	Center Point?	Total number of runs	Block(s)
General full factorial	Full	108	3	Not applicable	324	No blocks

Fig. 9. General full factorial DoE

Figure 10 depicts a full factorial DoE, which would reduce the number of runs to 99 by eliminating any in between levels. The number of runs required went down drastically, yet still remained unrealistically high and this DoE would also not be approved for financial reasons.

Response Variable(s)			R/S Efficiency , R/S Volume, L/S Efficiency, and L/S Volume			
Factor			Level 1	Level 2	Level 3	Level 4
R/S body entrance diameter			14	24	Not applicable	Not applicable
R/S body entrance diameter surface roughness			70	140	Not applicable	Not applicable
R/S body distance flange to ridge as percent of diameter			4	10	Not applicable	Not applicable
L/S body exit diameter			18	26	Not applicable	Not applicable
L/S body exit diameter surface roughness			70	140	Not applicable	Not applicable
Type of DoE	Resolution Type	Number of Runs	Number of replicates	Center Point?	Total number of runs	Block(s)
Full factorial	Full	32	3	3	99	No blocks

Fig. 10. Full factorial DoE

A fractional factorial DoE with resolution V is shown in Figure 11. Here, information would be lost due to the lower resolution, but the number of runs required also went down by almost fifty percent when compared to a full factorial DoE. This would be clearly less expensive than a full factorial DoE and yet expected to lead to important improvements.

Response Variable(s)			R/S Efficiency , R/S Volume, L/S Efficiency, and L/S Volume			
Factor			Level 1	Level 2	Level 3	Level 4
R/S body entrance diameter			14	24	Not applicable	Not applicable
R/S body entrance diameter surface roughness			70	140	Not applicable	Not applicable
R/S body distance flange to ridge as percent of diameter			4	10	Not applicable	Not applicable
L/S body exit diameter			18	26	Not applicable	Not applicable
L/S body exit diameter surface roughness			70	140	Not applicable	Not applicable
Type of DoE	Resolution Type	Number of Runs	Number of replicates	Center Point?	Total number of runs	Block(s)
Fractional factorial	(V)	16	3	3	51	No blocks

Fig. 11. Fractional factorial DoE with resolution V

A fractional factorial DoE with resolution III is shown in Figure 12. This DoE has the worst resolution; therefore, interactions could be confounded.

Response Variable(s)			R/S Efficiency , R/S Volume, L/S Efficiency, and L/S Volume			
Factor			Level 1	Level 2	Level 3	Level 4
R/S body entrance diameter			14	24	Not applicable	Not applicable
R/S body entrance diameter surface roughness			70	140	Not applicable	Not applicable
R/S body distance flange to ridge as percent of diameter			4	10	Not applicable	Not applicable
L/S body exit diameter			18	26	Not applicable	Not applicable
L/S body exit diameter surface roughness			70	140	Not applicable	Not applicable
Type of DoE	Resolution Type	Number of Runs	Number of replicates	Center Point?	Total number of runs	Block(s)
Fractional factorial	(III)	8	3	3	27	No blocks

Fig. 12. Fractional factorial DoE with resolution III

But, only 27 runs are required and this is the option most likely to get an approval form a cost perspective. With this option, the team could make a better case for gaining approval from the champion.

The DoE planning got off to a rough start due to jumping right in with only a problem statement, which was not actually available during the initial planning session. Placing the statement in the same document that was used for planning helped to ensure that the problem statement and objectives would always be available when needed.

Using the p-diagram helped greatly with gaining insights into the situation under consideration and this simplified the identification of response variables, factors, and levels. After proper planning, the number of required runs was reduced from 1 536 with (3 replicates) to a more realistic 27, which includes 3 replicates with only 8 runs each and 1 center point per replicate. This DoE would cost around 135,000 Euro; however, the information gained was considered to be worth this investment.

Discussion

An engineer attempted to plan a DoE and ended up with a plan that would require far too many runs to actually perform the DoE and a cost that would run into millions of Euro. Some of the planned DoE runs would have required combinations of parts that were impossible to make; better planning was needed, and therefore, a planning worksheet was created with a p-diagram for displaying noise factors, input factors, input factors, error states, and the ideal function of the system.

The p-diagram made potential factors visible and helped with successfully planning a DoE. Therefore, the authors recommend using a p-diagram in a planning worksheet when planning a DoE. However, providing training in the use of the worksheet and p-diagram is advisable.

A consideration for future research would be to plan a study comparing the use of a p-diagram by professionals in industry to professionals in industry planning a DoE without a p-diagram.

Conclusions

Statisticians and other statistics practitioners such as Lean Six Sigma Black Belts and quality engineers are often called upon to work together with SMEs to perform DoEs. A p-diagram will not be helpful if the correct information is not entered into it. Subject matter knowledge is important when planning and performing experiments (Box et al., 2005). The statistician may have mastered DoE; however, the SME's input may be critical in determining the correct factors, levels, and response variable of interest. The SME may be an engineer or even the machine operator responsible for the daily activities at the process that is being considered for a DoE. They may not understand what a DoE is or what is needed for a DoE. To facilitate DoE planning, a p-diagram may be helpful in such a context, as demonstrated by the case study and other examples shown.

In this case study, an engineer initially planned DoEs that would have been too costly to perform, so a worksheet was used with a p-diagram to assist in DoE planning. The worksheet ensured the actual problem statement was visible during planning and also made it clear that some initially considered DoEs would have involved part combinations that would never be used in series production and were therefore irrelevant. The p-diagram helped to ensure that factors and levels were not confused. With the p-diagram, a realistic DoE was planned.

Using a p-diagram also helped to facilitate communication while planning the DoE by providing an organized place to list all identified options for factors, levels, and possible response variables. A list of potential noise factors may have also been useful due to making clear potential influences that could negatively impact the DoE.

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