BLOCK DESIGN EXPERIMENTS TO ANALYZE EXECUTION RATES ACROSS FIVE MACHINES

DISEÑO DE EXPERIMENTOS POR BLOQUES PARA ANALIZAR LAS TASAS DE EJECUCIÓN DE CINCO MÁQUINAS

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Reception: 30/April/2025 **Acceptance**: 27/November/2025

Abstract

This study presents an analysis of the execution rate behavior across five different machines. And contributes to understanding machine performance variability using a statistical block design. For which a complete two-factor block design was made: the machine as the treatment of interest and the operator as a block with five levels each. The software used in statistical analysis is Minitab®. The results show that the machine is a significant factor for the execution rate while the operators are not.
Keywords: ANOVA, block design, design of experiments, execution rate, machine performance, minitab®.

Resumen

Este estudio presenta un análisis del comportamiento de la tasa de ejecución de cinco máquinas. Y contribuye a entender el comportamiento de la variabilidad usando diseños estadísticos por bloques. Para ello, se llevó a cabo un diseño completo de bloques de dos factores: la máquina como tratamiento de interés y el operario como bloque con cinco niveles cada uno. El software utilizado en el análisis

estadístico es Minitab®. Los resultados muestran que la máquina es un factor importante para la tasa de ejecución, mientras que los operadores no lo son.
Palabras clave: *ANOVA, diseño de bloques, minitab®, rendimiento de la maquina, diseño de experimentos, tasa de ejecución.*

1. Introduction

Experimental designs are frequently used during research; be it academic, scientific, in general in all social sciences, due to its systematic process that begins with the planning of the project, then with the execution and to later carry out the analysis so that, as [Gutiérrez et al., 2009] point out, the data collected "have statistical validity in order to obtain valid and useful conclusions" [p.17]. that supports the study of the effect of certain variables on one or more response variables that represent a phenomenon of interest.

In experimental design, a block design groups experimental units into "blocks" according to similar characteristics, with the purpose of reducing the effect of systematic variations or "nuisance factors" that are not of primary interest. This approach constitutes a fundamental technique, widely used in industrial experimentation [Montgomery, 2004]. In particular, the randomized block design is frequently employed to minimize the effect of variability when it is associated with discrete units (e.g., location, operator, plant, batch, time) [Minitab®]. Various applications of experimental designs with blocks are presented in the literature, among which the following stand out: [Calderón-Andrade et al., 2020] discuss the application of randomized complete block designs in industrial studies, focusing particularly on the structure of process comparaisons. In their study, this involves two decoration lines operating under similar conditions but differing in design and workflow. [Ahn et al., 2024] present a systems study that measures performance (throughput) and uses measurement and clustering techniques to separate on-/off-CPU effects; it is a recent and good example of how to structure performance experiments in the presence of multiple sources of variation. [Shirke et al,. 2024] provides a comprehensive review of computational storage and system performance, highlighting metrics such as throughput and examining how various system factors affect them. The study serves as a reference for identifying factors that may be used as blocks or sources of blocking in experimental design.

To reinforce the analysis and determine whether any of the factors had an effect on the response variable, the main effects graph was used, which indicates whether the study factor is significant for the variable. The steeper the slope of the line, the greater the magnitude of the main effect [León & Montero, 2001].

Blocking is a means of reducing and controlling experimental error variance in order to achieve greater precision. [Frías-Navarro and Pascual-Soler, 2021] mention that blocking variables are introduced into the design's structural equation as a source of variance that is not part of the study's substantive hypothesis, but as a result, their effect is controlled and the model's error term is reduced [p. 404]. [Minitab 2017] clarifies that in the realm of experimental design, measurements that are repeated are taken from experimental sessions that share the same configuration but are conducted separately. This differs from repetitions, which refer to direct observations under identical circumstances. Replicated measurements can help in estimating variance (experimental error) that arises from slightly varying experimental settings. Such experimental errors provide a basis for assessing if the differences noticed in the data hold statistical relevance.To capture and gauge all variations in the experiment, it is essential to randomize replications to encompass the full spectrum of experimental conditions. If the total number of experimental runs is excessive to manage under uniform conditions, blocks of replication may be established. By forming blocks, one can assess the impacts of these blocks separately from the experimental error.

Some factors to consider regarding replications include:

- Screening designs that aim to minimize an extensive array of factors usually do not utiliza several replications.
- If your goal is to create a predictive model, having multiple replications can enhance its accuracy.
- The resource at your disposal may influence how many replications you are able to perform. For instance, if your experiment is very expensive, you might only have the opportunity to conduct it a single time.

- A larger volume of data allows for the detection of minor effects or provides more capacity to identify an effect of a constant magnitude.

For the purposes of this study, the design is exploratory and intended for initial validation. It is aimed at understanding the effects of the machines on the response variables, and only one replication was chosen to make efficient use of the budget and available resources.

The block design experiment presented in this study is made up of two fixed factors each with five levels, giving a total of twenty five experimental runs. The response variable is the execution rate. The values designated for the machine factor are: machine 1 (C01), machine 2 (C02), machine 3 (C03), machine 4 (C04) and machine 5 (C05) and the corresponding values for the Operator factor correspond to the five operators (OPE1, OPE2, OPE3, OPE4, OPE5).

2. Methods

To accomplish the objective of this study, the methodology was structured around the following 4 stages:

- Stage 1. Definition and planning of the experiment matrix. The purpose is to determine if the machine has an inference about the execution rate. Table 1 shows the details of the design where two study factors have been defined for: The machine (as a treatment factor with five levels) and the operator (as a block factor with five levels).

Table 1 Factor vs design levels.

Factor	**Levels**
Operator	OPE1, OPE2, OPE3, OPE4, OPE5
Machine	C01, C02, C03, C04, C05

Source: Own elaboration.

- Stage 2. Execution. In this stage, each operator interacts randomly with each machine (one repetition) this is a general rule [Badii et al., 2017]; it is more efficient to have a single repetition of each treatment per block, so a total of

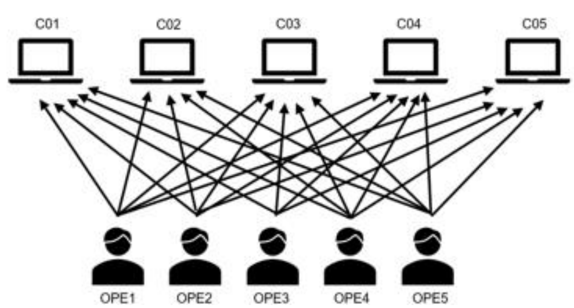
25 observations were made. Table 2 presents the matrix of the complete experimental design.

Table 2 Complete experimental design.

Run	Block	Operator factor	Machine Factor
1	Block 1	OPE1	C01
2		OPE1	C02
3		OPE1	C03
4		OPE1	C04
5		OPE1	C05
6	Block 2	OPE2	C01
7		OPE2	C02
8		OPE2	C03
9		OPE2	C04
10		OPE2	C05
11	Block 3	OPE3	C01
12		OPE3	C02
13		OPE3	C03
14		OPE3	C04
15		OPE3	C05
16	Block 4	OPE4	C01
17		OPE4	C02
18		OPE4	C03
19		OPE4	C04
20		OPE4	C05
21	Block 5	OPE5	C01
22		OPE5	C02
23		OPE5	C03
24		OPE5	C04
25		OPE5	C05

Source: Own elaboration.

- Stage 3. Figure 1 outlines the setup of the experiment 5 operators and 5 machines from different suppliers alternated randomly during the experiment.



Source: Own elaboration.

Figure 1 Assignment of each operator to each computer (random).

- Stage 4. Statistical analysis. In this stage, the observations resulting from the experiment are subjected to statistical analysis in the Minitab® software.

Minitab® is widely recognized for its intuitiveness and accessibility, even for researchers with basic atatistical knowledge. The use of Minitab® allowed the automation of mathematical calculations, reducing errors that could arise when performing this procedure manually.

The hypotheses to be tested are the following:

- ✓ In Equation 1 and Equation 2 the hypothesis for the Operator's Treatment is raised.

$$H_0: A_j = 0, para\ todo\ valor\ de\ j, (No\ afecta) \quad (1)$$

$$H_1: A_j \neq 0, para\ al\ menos\ un\ valor\ de\ j, (Sí\ afecta) \quad (2)$$

- ✓ In Equation 3 and Equation 4 the hypothesis of Machine Treatment is raised.

$$H_0: B_j = 0, para\ todo\ valor\ de\ j, (No\ afecta) \quad (3)$$

$$H_1: B_j \neq 0, para\ al\ menos\ un\ valor\ de\ j, (Sí\ afecta) \quad (4)$$

- ✓ Equation 5 is used which describes the rejection criterion where the following will be used: $\alpha = 0.05$.

$$Si\ \ Valor\ P < \alpha, \qquad se\ rechaza\ H_0 \quad (5)$$

3. Results

Table 3 presents the matrix of the complete experimental design, as well as the execution rate obtained in each run.

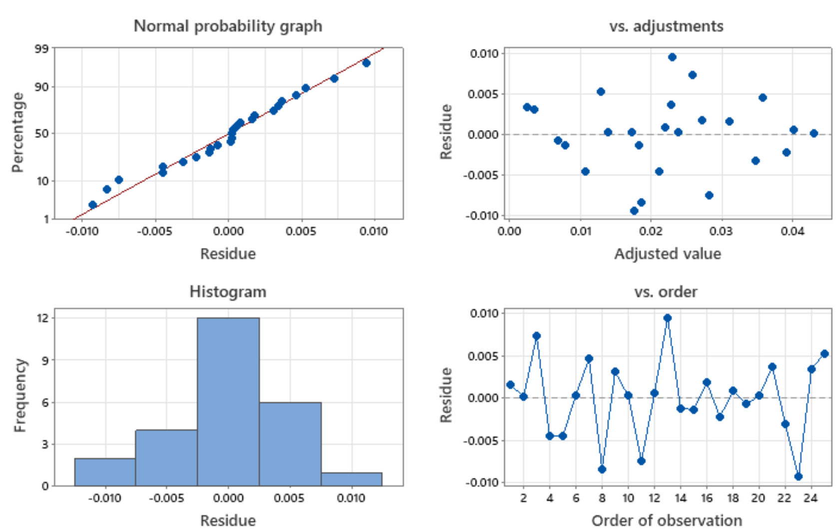
Figure 2 shows the graph where the following observations can be made: the normal probability plot of the residues proves the assumption that the residues are normally distributed. The residuals vs. adjustments graph presents a behavior such that it is possible to verify the assumption that the residuals have a constant variance. The residuals histogram shows symmetry in the residuals, the residuals graph against time. Thus, there is no reason to suspect any violation of the assumptions of independence or of constant variance.

Based on the results obtained in Table 4, for the effect of the machine factor, given that the value of $p = 0$ therefore ≤ 0.05, then the null hypothesis is rejected, and it is concluded that there is a significant difference in the machines in terms of their effect on the execution rate. While for the operator $p = 0.179$ therefore the null hypothesis is accepted, concluding that there is no significant difference. Table 5 shows that the variance of the data is 0.00561564, while R^2 responds to a capture in the model of 85.91% of the variation and adjusted R^2 of 78.8%

Table 3 Matrix of the complete experimental design and response.

Run	Block	Operator factor	Machine Factor	Execution rate
1	Block 1	OPE1	C01	0.0327225
2		OPE1	C02	0.0431406
3		OPE1	C03	0.0331345
4		OPE1	C04	0.0062500
5		OPE1	C05	0.0166667
6	Block 2	OPE2	C01	0.0241663
7		OPE2	C02	0.0403063
8		OPE2	C03	0.0102302
9		OPE2	C04	0.0065368
10		OPE2	C05	0.0140845
11	Block 3	OPE3	C01	0.0207857
12		OPE3	C02	0.0406835
13		OPE3	C03	0.0324992
14		OPE3	C04	0.0066667
15		OPE3	C05	0.0169492
16	Block 4	OPE4	C01	0.0290360
17		OPE4	C02	0.0369140
18		OPE4	C03	0.0228258
19		OPE4	C04	0.0061538
20		OPE4	C05	0.0175439
21	Block 5	OPE5	C01	0.0265604
22		OPE5	C02	0.0316356
23		OPE5	C03	0.0083243
24		OPE5	C04	0.0059471
25		OPE5	C05	0.0181818

Source: Own elaboration.



Source: Own elaboration.

Figure 2 Residual plots for execution rate in Minitab®.

Table 4 ANOVA Table.

Source	GL	SC Ajust.	MC Ajust.	p value
Operator	4	0.00022657	0.00005664	0.179
Machine	4	0.00284910	0.00071227	0.000
Error	16	0.00050457	0.00003154	
Total	24	0.00358024		

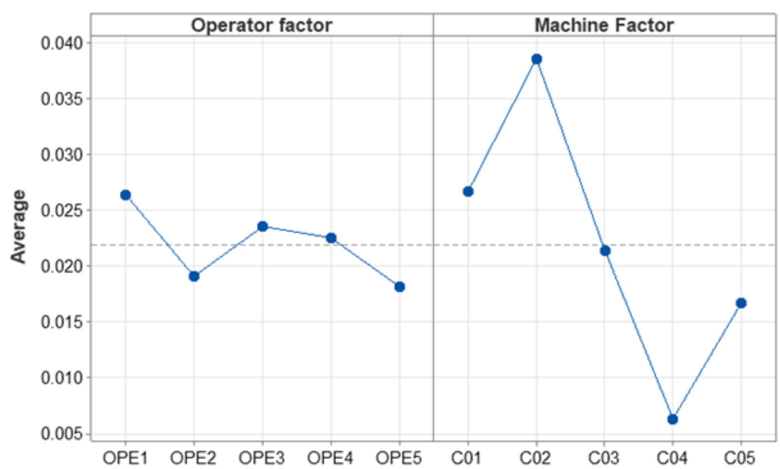
Source: Own elaboration.

Table 5 Variance, R^2 and $R^2 - Adjusted$.

Parameter	Value
Variance	0.00561564
R^2	85.91
$R^2 - Adjusted$	78.8

Source: Own elaboration.

Figure 3 shows the graphs for main effects where it is reiterated that there is no significant difference for the operator factor while there is a significant difference in the machine factor (showing a steep slope).



Source: Own elaboration.

Figure 3 Main effects plot for Execution rate in Minitab®.

4. Discussion

When performing the analysis using statistical tools such as the following:

- Validation of residual assumptions.
- ANOVA for block design.
- Graphical analysis of main effects.

It allowed through simple steps the application of an experimental strategy that facilitates decision-making.

5. Conclusions

In this experiment it was considered that the operator treatment could add variation, therefore, it was blocked. Once the statistical analysis was carried out, it was recognized that the only factor that presents significance are machines.

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