Definition of strategies based on simulation and design of experiments

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ABSTRACT

Nowadays, even fairly small companies have to use more and more efficient working methodologies such as the "transnational" ones. The market may still be local or regional, but the competition is global. Companies, to be competitive, need to market their products at acceptable prices, in the right time and with a higher level of quality. According to some authors, the company's survival strategy involves the development of methodologies that are capable of designing, developing and / or improving the processes so that they are more efficient, with a low cost and in a shorter time. This article begins by discussing the relevance of the theme to the competitiveness of companies. Next, it is discussed how the Design of Experiments associated with simulation tools can contribute to the definition of operational strategies. Finally, an illustrative example is presented, and the main conclusions are drawn.

INTRODUCTION

Currently, at the macroeconomic level, it is possible to identify a set of variables that influence the operational strategies developed by managers, such as the energy crisis associated with the constant increase of oil prices and the emergence of new trading powers, as is the case of China and India, which have created new threats to the European industry (Martins et al. 2018). To be competitive, companies must develop capacities that enable them to respond quickly to market needs. Nowadays, it is possible to identify several variables that influence the development of production processes such as market pressures for quality improvement, reduction of production time and costs, and increased agility in production (Camarinha-Matos et al. 2004; Abreu and Calado 2017). On the other hand, the product life cycle is shorter and shorter, which means that the pace of design and/or development of new products is accelerating. The most frequent introduction in the market of new products with shorter time periods has been, in recent times, the survival strategy of some companies to win new customers and respond to the diversity of options available in the market. Therefore, the search for excellence in the creation of more efficient processes has become an operational survival strategy for companies competing in a globalized word (Abreu and Urze 2016; Abreu et al. 2018; Requeijo et al. 2014).

One of the goals of the twenty-first century organizations is to produce consistent products and robust to noise, i.e., the processes should present a good capacity and are aligned with the technical specifications and exhibit reduced variability. Reducing variability, i.e. reducing the common causes of variation due to the various sources of variation that are always present in the production processes, is basically achieved through two interventions. The first refers to more significant reductions, through the intervention of top management in the change of some of the resources allocated to the processes, such as new equipment, more qualified suppliers, more effective training of the organization's employees. A second, when it is not possible to resort to new financial resources, is to reduce some of the variability by optimizing the levels of factors (controllable variables) present in the productive processes.

These are the principles of the approach suggested in this paper, Design of Experiments (DOE) (Pereira and Requeijo 2012; Montgomery 2017; Taguchi 1986; Peace 1993). According to some authors (Harrison et al. 2007; Altiok and Melamed 2010; Klimov and Merkureyv 2008), the increasing use of simulation techniques is related to the fact that through simulation it is possible to imitate the operation of the real system in detail and predict its behaviour even when new events are introduced in the model, answering questions such as: What-If.

In addition, through the simulation, it is also possible to perform analyses on systems that do not yet exist, which allows the development of more efficient systems before any physical alteration has been initiated.

This paper discusses the advantages of DOE in articulation with simulation tools, to identify the most important variables in relation to a given objective and how they interact with one another and with the other elements of the system.

FUNDAMENTALS OF DESIGN OF EXPERIMENTS

The Design of Experiments (DOE) is a methodology that allows us to select the best combination of factors levels in order to optimize the value (s) of the quality characteristic (s) under study, both in terms of its mean value such as the reduction of variability, i.e., allows to determine which controllable factors affect certain quality characteristics and which are the best levels of these factors in order to increase the resistance of the product to the noise factors, thus satisfying the requirements of the various stakeholders in the performance of an organization.

Any Design of Experiments requires, prior to its implementation, a systematic approach so that its implementation leads to positive results. Generally, such an approach should include the following points [7,8]: Constitution of the research team; Clear definition of the objectives of the experiments; Background analysis; Selection of answers, i.e., choice of quality features as well as the respective measurement methods; Selection of controllable factors to be tested and their levels and, if feasible, choice of noise factors and their corresponding levels; Prior analysis of possible interactions between factors, understanding that there is an interaction between two factors when the effect of one factor on the response depends on the level of the other factor; Identification of the factors that will remain constant during the experimentation; Definition of the number of experiments to be performed and, depending on this decision and the number of factors and levels, plan the experiment using the most appropriate matrix, i.e. define the experimental layout; Definition the number of replications (number of times that a particular experiment is repeated); Execution of the experiments (tests) randomly.

The choice of the design of experiment is a function of the number of factors and the levels of those factors. Usually, fractioned planning is used, i.e. design in which only part of the total possible combinations is studied, which allows a significant cost reduction. In this article, only a full factorial design is presented, with two-level factors, referred to as 2k, where k represents the total number of factors.

The 2k Factorial Design

The full factorial design includes all possible combinations of the factors' levels. The simplest factorial design is one in which each factor is studied only at two levels. The generic representation of this type of design is 2k, where 2 is the number of levels of each factor and k is the number of factors included in the design. A complete factorial with two factors, A and B, where each is tested at two levels, will therefore be a 22, which requires 4 experiments to study all possible combinations of levels of the two factors.

The planning matrix of this design is shown in Table 1. To identify which effects, factors and interaction, influence significantly the response, is used the statistical technique ANOVA (Analysis of Variance). For this, it is necessary to determine the variations due to each factor/interaction related with the corresponding application of the proposed approach.

The variation of factor X (SS - Sum of squares) is determined as follows:

Table 1: 2^2 Factorial Design Planning Matrix

Standard Order	*A*	*B*	Response
(1)	–	–	$y_{11} \ldots y_{1n}$
a	+	–	$y_{21} \ldots y_{2n}$
b	–	+	$y_{31} \ldots y_{3n}$
ab	+	+	$y_{41} \ldots y_{4n}$

$$SS_X = \frac{[(\sum y)_{X^+} - (\sum y)_{X^-}]^2}{2^k n} \tag{1}$$

Where: n-number of replicates

The effect of the factor (the mean effect of a factor is the change in response caused by a change in the level of that factor) is given by:

$$\text{Effect of Factor } X = \frac{(\sum y)_{X^+} - (\sum y)_{X^-}}{2^{k-1} n} \tag{2}$$

The contrast of a factor or interaction is calculated from the response values of the various replicates of the experiment. For example, the contrast of the factor *A* is given by

$$\text{Contrast of } A = -\sum_{j=1}^{n} y_{1j} + \sum_{j=1}^{n} y_{2j} - \sum_{j=1}^{n} y_{3j} + \sum_{j=1}^{n} y_{4j} \tag{3}$$

The ANOVA table for the factorial design 2^2 is given as a function of the main factors and the interaction, as shown in Table 2.

Table 2 - ANOVA Table for 2^2 Factorial Design

Source of Variation	SS_X	*Deg. of Freedom* ν_X	*Mean Square* MS_X	F_0
A	SS_A	1	SS_A/ν_A	MS_A/MS_{Error}
B	SS_B	1	SS_B/ν_B	MS_B/MS_{Error}
AB	SS_{AB}	1	SS_{AB}/ν_{AB}	MS_{AB}/MS_{Error}
Error	SS_{Error}	$(2^k n - 1) - 3$	SS_{Error}/ν_{Error}	
Total	SS_T	$(2^k n - 1)$		

The total variation (SS_T) and the residual variation are given as follows:

$$SS_T = \sum_{i=1}^{2^k} \sum_{j=1}^{n} y_{ij}^2 - \frac{\left(\sum_{i=1}^{2^k} \sum_{j=1}^{n} y_{ij}\right)^2}{2^k n} \tag{4}$$

$$SS_{Error} = SS_T - \sum SS_X \tag{5}$$

The best levels of factors are determined by analysing the mean response values, for the high level (+) and for the low level (–), of the significant factors/interaction. Thus, one should choose the level that optimizes the response, e.g., if the response (quality characteristic) is of the type the higher the better, the best level is one that maximizes the value of the responses. When studying the best combination of factors levels of a factorial design, it is convenient to analyse the response surfaces of the significant interactions.

DOE Assumptions

The validation of the analysis of the results of a design of experiments using the ANOVA application requires the verification of certain assumptions, without which all the analysis can be biased. In addition to applying the correct mathematical model, we analyse the errors, or residues, for each value of the experimentation. It should always be checked whether such assumptions are true, namely if the errors are independent and are normally distributed with null mean and constant variance σ^2. Residual analysis allows to make such confirmation. The residues are obtained by the difference between the values observed and the corresponding values expected or estimated by the model, defined by the following equation:

$$e_{ij} = y_{ij} - \hat{y}_{ij} = y_{ij} - \bar{Y}_{i.} \tag{6}$$

If the assumptions of Normality and homogeneity of variance are not verified, the original data should be transformed and the analysis of variance of the transformed data should be performed. There are several ways to proceed with this transformation, such as the empirical method and the transformation of Box and Cox [7,8].

Contribution of Factors

Taguchi [9,10] attaches great importance to the percentage contribution of a factor or an interaction to the Total Variation, a concept that is used in the analysis of variance as a complement to the test F. The evaluation of the significance of a certain factor X is carried out by the comparison between the Mean Square of the factor and the Residual Variance, that is:

$$\boldsymbol{F_0} = \frac{\boldsymbol{MS_X}}{\boldsymbol{MS_{Error}}} = \frac{\boldsymbol{SS_X}}{(g.l.)_X \times \boldsymbol{MS_{Error}}} \tag{7}$$

If the factor *X* is not significant, its mean variation MS_X will be of the same order of magnitude of the residual variation. Thus, Taguchi defines the contribution percentage of a factor or an interaction by the following equation:

$$\boldsymbol{\rho_X} = \frac{\boldsymbol{SS_X} - (g.l.)_X \times \boldsymbol{MS_{Error}}}{\boldsymbol{SS_T}} \times \mathbf{100} \tag{8}$$

In the above equation, ρ_X is the percentage contribution of the factor *X*, SS_X the variation of factor *X*, $(g.l.)_X$ the degrees of freedom of the factor *X*, MS_{Error} the residual variance and SS_T the total variation.
The contributions of significant factors are usually presented in the ANOVA table. The value of the error contribution is of practical interest, since a high value of the error may mean that there were problems in the application of the methodology, such as, for example, exclusion of potentially important factors from experimental planning, errors made during the execution of experiments or poor analysis of the results. After analysis of variance, the mean responses for each level of factors and / or significant interactions are examined and the levels leading to the pursuit of the previously defined objectives are chosen.

APPLICATION EXAMPLE

To illustrate the advantages of using DOE and simulation to understand the performance of the systems, as measured by one or more relevant variables, when one or more controllable variables or even non-controllable variables are observed, the case described in section 3.1 is considered.

Simulation scenario

A manufacturing cell consists of two serial workstations, a machining station and an inspection station. At the machining station, the semi-finished products are manufactured and sent to the inspection station. Transportation times between the two seasons are negligible. After the inspection the products are sent for shipment. However, it was found in the inspection process that 10% of the products did not meet the customer's requirements and returned to the machining centre for reprocessing.
Consider the following operational data: The products arrive at the machining station with a Takt Time of 1 minute/unit; The machining time follows a uniform distribution in which the minimum and maximum durations are UNIF (0.65; 0.70) minutes; The inspection time follows a uniform distribution in which the minimum and maximum durations are UNIF (0.75; 0.80) minutes. According to historical data the available maintenance times associated with the machining centre are as follows: MTBF – “Mean Time Between Failures”, was estimated to be a random variable that can be described by an exponential distribution, EXPO (360), with a mean of 360 minutes; The equipment repair time, "Down time", was estimated as a random variable following a uniform distribution in which the minimum and maximum durations are UNIF (8; 12) minutes.
Due to the market pressure, the company needs to reduce lead time, i.e. the total time to carry out the machining and inspection process and thus increase its competitiveness. After several analyses, three improvement strategies are considered. According to the Maintenance perspective, with the introduction of a new maintenance management policy, there are strong expectations that it is possible to increase the time interval between equipment malfunctions, that is, it was defined as an expected result as a random variable which can be described by an exponential distribution with a mean of 400 minutes and the equipment repair time, "Down time", was defined as an expected result as being a random variable that follows a uniform distribution in which the minimum and maximum duration is UNIF (6; 9) minutes.
In terms of quality, through the implementation of a quality improvement program the expectations would be to obtain a reduction in the rejected product rate of 5% and thus reduce “Lead Time”. Finally, in the production perspective, through better production management it would be possible to obtain significant improvements in the production / inspection process in relation to the current scenario. The machining time would then follow a uniform distribution in which the minimum and maximum durations are (0.55; 0.60) minutes and the inspection time would then follow a uniform distribution in which the minimum and maximum durations are (0, 60; 0.70) minutes.
Thus, to identify the improvement actions that should be implemented, and its degree of urgency, that allow to reduce

the “Lead Time”, a simulation model was built in the Arena software (www.arenasimulation.com) as illustrated in Figure 1 and experiment planning was applied, where five control variables (factors) were considered as shown in Table 3 to analyse their impact on the response variable "Lead Time".

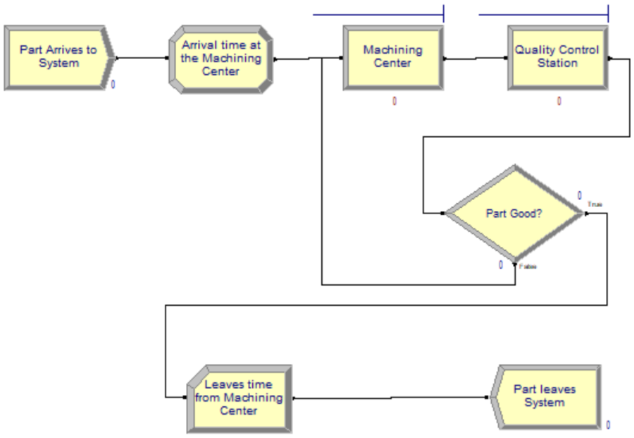

Figure 1: Arena Simulation Model

Table 3: Factors to Consider in the Analysis of the Response Variable "Lead Time"

FACTOR	DESCRIPTION	CURRENT LEVEL (-1)	PROPOSED LEVEL (+1)
A	Time between equipment malfunctions	EXPO (360) min	EXPO (400) min
B	Equipment repair time	UNIF (8,12) min	UNIF (6, 9) min
C	Rejected products	10%	5%
D	Processing time	UNIF (0.65; 0.70) min	UNIF (0.55; 0.60) min
E	Inspection time	UNIF (0.70; 0.80) min	UNIF (0.60; 0.70) min

The simulation time used was 160 hours (approximately 20 days of production) with a warm-up period to ensure the system is loaded and three replications were performed for each experiment.

Analysis of results

The value for each replica of the experiments was obtained by simulation, as mentioned in section 3.1. To find the best combination of levels of the factors that improve the response (Lead time) the ANOVA statistical technique was applied. Thus, the first step consists of the construction of the condensed ANOVA and to verify the assumptions of the ANOVA.

Since the Normality and homogeneity of variance are not verified, the experimental data had to be transformed using the Box and Cox transformation. Statistica software was used to perform this task. Table 4 shows the condensed ANOVA of the complete factorial 25 of the transformed data, referring to “Lead Time”.

The best levels of factors are determined taking into account the significant effects. The mean values of the transformed data of the significant factors are presented in Table 5 for the low (- 1) and high (+ 1) levels. Figure 2 shows the response surfaces of the significant interactions.

Analysing the results presented in Table 5 and Figure 2, Table 6 shows the best levels of factors for the study performed.

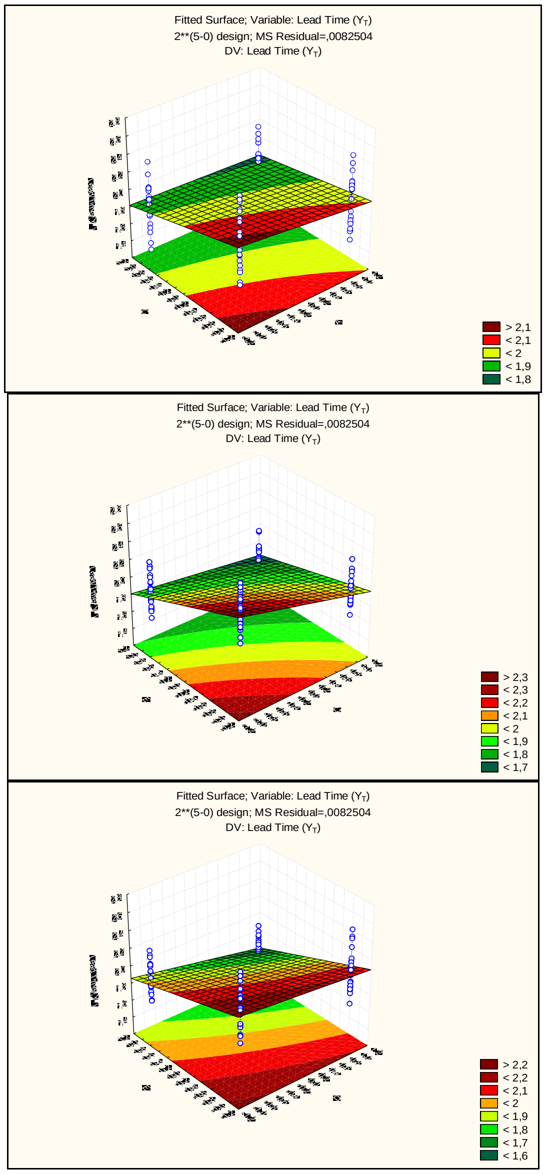

Figure 2: Response Surfaces of Significant Interactions for “Lead Time” (Factorial 2^5) – AC, CE and DE

Table 4: Condensed ANOVA of Factorial 2^5 for “Lead Time”

	ANOVA; Var.:Lead Time (Y_T); R-sqr=0.90573; Adj:0.89706 (Full Factorial 2^5 (n=3)) 2**(5-0) design; MS Residual=,0082504 DV: Lead Time (Y_T)					
Variation source	SS_X	ν_X	MS_X	F_0	p	ρ (%)
A	0.189510	1	0.189510	22.9697	0.000007	2.38%
B	1.067038	1	1.067038	129.3312	0.000000	13.91%
C	1.346961	1	1.346961	163.2594	0.000000	17.58%
D	0.775235	1	0.775235	93.9630	0.000000	10.07%
E	3.305693	1	3.305693	400.6691	0.000000	43.31%
AC	0.043639	1	0.043639	5.2893	0.023851	0.46%
CE	0.114611	1	0.114611	13.8915	0.000344	1.40%
DE	0.053526	1	0.053526	6.4876	0.012621	0.59%
Error	0.717787	87	0.008250			10.30%
Total	7.613999	95				100%

Table 5: Mean Values of Transformed Data for "Lead Time" (Factorial 2^5)

Factor	*A*	*B*	*C*	*D*	*E*
Level -1	1.9836	2.04459	2.05762	2.0290	2.12473
Level +1	1.8947	1.83374	1.82071	1.8493	1.75360

Table 6: Best Levels of the Factors for the "Lead Time" (Factorial 2^5)

A	*B*	*C*	*D*	*E*
1	1	1	1	1

CONCLUSIONS

Companies must be lucid, otherwise it can be fatal today, that in order to be competitive the strategy of survival must be based on methodologies that are capable of identifying the actions that must be carried out in order to provide, through efficient processes, innovative products and high quality. Thus, the definition of operational strategies based on techniques such as those presented in this article is more rigorous, avoiding in this way the subjectivity of analysis.

In this context, it was discussed how the experiments planning supported in simulation processes can be used in the definition of operational strategies in an organizational context.

However, one aspect that may compromise the robustness of the improvements resulting from the implementation of the operational plan, once designed, is related to the initial improvement expectations that would be expected to obtain (future state) in each of the actions (factors) identified.

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