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ECONOMIC EVALUATION OF THE INCREASE IN PRODUCTION CAPACITY OF A HIGH TECHNOLOGY PRODUCTS MANUFACTURING CELL USING DISCRETE EVENT SIMULATION

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ABSTRACT

This paper presents an application of the modeling and simulation methodology along with the Design of Experiments (DOE) to aid the decision makers to know the economic risk they are taking when there are many scenarios. Firstly, the production process was studied and documented by a SIPOC, an IDEF0 and a Flowchart. These techniques were combined to elaborate the simulation conceptual model. After that, the probability distributions were chosen and fed the computer model, built to emulate the real system. The simulation model was verified and statistically validated. Sixty four possible scenarios were tested, and in this case, the DOE may contribute to select the scenarios which are relevant to the economic analysis. The simulator used was Promodel® which provided the output to fed the cash flow of each scenario. Finally, the Net Present Value (NPV) and the economic risk of each scenario were calculated.

1 INTRODUCTION

The real systems usually present great complexity mainly due to its dynamic nature (that is, it changes its state during the time) and its random nature (that is, it is governed by random variables). The simulation model achieves to capture these characteristics with more accuracy, attempting to reproduce in a computer the same behavior that the system would show if under the equal form conditions. Particularly, the simulation model is used as a tool for getting answers to sentences like: 'What if…' (Chwif and Medina 2007).

As stated by Banks et al. (2005), computational simulation is more widely used in manufacturing systems than in any other area. Additionally, O'Kane, Spenceley, and Taylor (2000) state that simulation has become one of the most popular techniques for the analysis of complex problems in manufacturing environments.

In accordance with Kelton (1999), the use of simulation aids directly the execution of experiments that are costly or even impossible to be carried out in practice.

According to Harrel, Ghosh, and Bowden (2000), computational simulation is the imitation of the current system, modeled in a computer to evaluate and improve its performance; that is, simulation is bringing reality to a controlled environment where its behavior can be studied under different situations, without involving great physical risks and costs.

For Shannon (1998), computational simulation is a powerful tool for process and complex system analysis, enabling the study, analysis and evaluation of situations that would not be possible in the real world. In a world of increasing competition, simulation has become an indispensable problem solving methodology for decision makers in many different areas.

The comparison of alternative systems is one of the most important uses of simulation (Banks et al. 2005). In this case of engineering economy problems, the alternative systems often take the form of alternative projects. Furthermore, these projects are often mutually exclusive. That is, the decision maker can choose only one of the alternative projects to invest in. Therefore, an analysis of the alternatives can be conducted to select the best investment. As the projects become more complex, simulation provides convenient and powerful means of conducting such analysis (Coates and Kuhl 2003).

Spedding and Sun (1999) have presented an application of discrete event simulation to the Activity Based Costing and they have suggested that a further analysis can determine the capital investment by taking into account the net cash flow over an extended period using the net present value technique.

Net Present Value is a measure of how much value is created or added to the current date for making an investment. Considering the goal of creating value to the shareholders, the capital budget process can be faced as a searching for investments with positive net present values (Ross, Westerfield, and Jordan 2002).

As referred to Nazzal, Mollaghasemi, and Anderson (2006), capital investment decisions are usually made using static and often deterministic models such as large spreadsheets, and/or mathematical optimization models, which use estimates from analytical models that tremendously simplify the fabrication operations.

In face of it, the main goal of this work is to build discrete event simulation models for a manufacturing cell and to present an economic evaluation of scenarios to the increasing in production capacity. As there are sixty four possible scenarios, the design of experiments is going to be used to select the most relevant scenarios to the economic analysis. In addition to that, we intend to know the economic risk associated with each analyzed scenario.

The main advantage in using a computer-based simulation model to reproduce a manufacturing system, in economic analysis like this, is that the model considers the randomness usually present in manufacturing systems and the evolution of this system along the time. In its turn, it can provide the production quantity to enter in the net cash flow with more accuracy in comparison to data based only the experience of a process specialist or arbitrary data.

This paper is organized as follows: in Section 2, the methodology observed in this work is presented. Section 3 brings the application of this methodology in a manufacturing cell of a Brazilian high technology company. Finally, Section 4 presents the conclusions.

2 METHODOLOGY

Chiwf and Medina (2007) present the simulation methodology in three phases: conception, implementation and analysis. In this methodology, there are three models that must be made: the conceptual model, the computational model and the operational model.

In the conception phase, the Project team defines the specific objectives and the model scope. Next, the conceptual model is built with the objective of representing the current system, making the construction of the simulation computational model easier. Some techniques that can be used in this phase are: the Value Stream Mapping (VSM) which is found in Abdulmalek and Rajgopal (2007), the IDEF-SIM proposed by Leal, Almeida, and Montevechi (2008), flowchart, process mapping, SIPOC, IDEF0 or even a combination of them, that is shown in Montevechi et al. (2008).

Once the conceptual model has been built and validated by the process specialists, the input variables (independents) and the output variables (dependents) can be defined. After that, the input data are collected and fitted to a probability distribution that feeds the computational model. In fact, the simulation model will be trustful if the data are.

In the implementation phase, the conceptual model is changed into a computational model through the programming in a simulator. After that, the computational model should go through two fundamental steps in a simulation study: the verification and the operational validation process.

The verification process consists in corroborating that a conceptual model was correctly translated into the computational model, while the operational validation process uses statistical techniques to compare the equality between the real and the simulation data.

Lastly, but not less important, the analysis phase. Once the model was verified and validated, it is capable of receiving experiments, inside the domain of validation. This is the more expected phase by the project team. Sanchez (2007) affirms that the process of building, verifying, and validating a simulation model can be arduous, but once it is complete, it is time to have the model work for the modeler. One extremely effective way of accomplishing this is to use experimental designs to help to explore your simulation model.

Figure 1 illustrates the methodology which was followed in this paper. It points out three possible techniques which are feasible to be used alone or even combined in the analysis phase: Design of Experiments (DOE), investment evaluation and economic risk analysis.

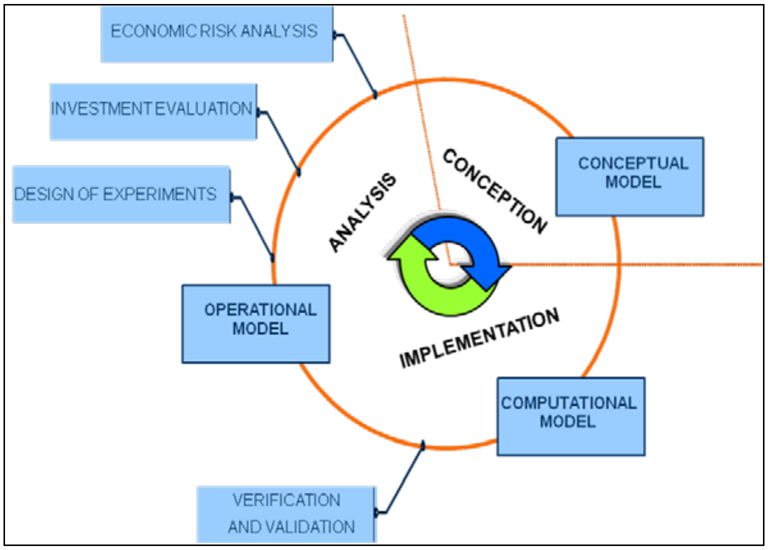


Figure 1: Simulation methodology, adapted from Chwif and Medina (2007)

Kleijnen et al. (2005) affirm that many simulation practitioners can get more from their analyses by using the statistical theory on design of experiments (DOE) specifically developed for exploring computer models. The benefits of the design of experiments in simulation include the possibility of improving the performance on the simulation process, as well as avoiding the trial and error techniques to seek solutions (Montevechi et al. 2007).

In simulation, the use of DOE has shown great impact in decision making support. Kelton (1999) affirms that design of simulated experiments offers a great deal of help, reducing time and effort by providing efficient ways to estimate the effects of changes of the model's inputs on the outputs.

When building a new factory, buying new pieces of equipment or simply renting a machine, that is, when investing in a new asset, a company must make an economic feasibility analysis on it, Casarotto and Kopittke (1998). This economic feasibility analysis may be proved through the criterion of the Net Present Value (NPV).

According to Van Groenendaal and Kleijnen (1997), NPV is often estimated for the most likely or base case scenario for model inputs, which gives an average NPV. This, however, is not considered sufficient information to help them assess the uncertainty of the result, needed to support their assessment of the project's economic risk.

The risk analysis considers the probability description of the input variables. Coates and Kuhl (2003) affirm that a lot of required information is uncertain, such as the actual cash flows from revenues and costs, the salvage value of equipment, the interest rate or even the project life. Probability descriptions of input variables and Monte Carlo sampling together provide a practical method of finding the distribution of the desired output given the various random and deterministic input variables.

3 APPLICATION

3.1 Conception

Since 2001, Padtec S/A has been a high technology Brazilian company specialized in Wavelength Division Multiplexing (WDM) transmission systems. Padtec has incorporated in its line of products, signal transport equipment according to OTN (Optical Transport Network) recommendations, reconfigurable optical add drop multiplexers (ROADM), multiprotocol traffic aggregator equipment, and an optical amplification solution for ultra long distance.

Padtec assembles equipments which form WDM optical systems and after it can install them. It was chosen a manufacturing cell which assemblies optical transponders. This product represents almost 40% of the company revenue, while the second product of major revenue corresponds to 20%.

In an effort to improve the understanding of the cell productive process, a diagram SIPOC, an IDEF0 and a flowchart were built and they were presented in Montevechi et al. (2008). The flowchart is presented in Figure 2 and it constitutes the simulation conceptual model which was shown to the process specialists (manager and operators), who said that it is a good representation of the real system. Therefore, the simulation conceptual model was validated.

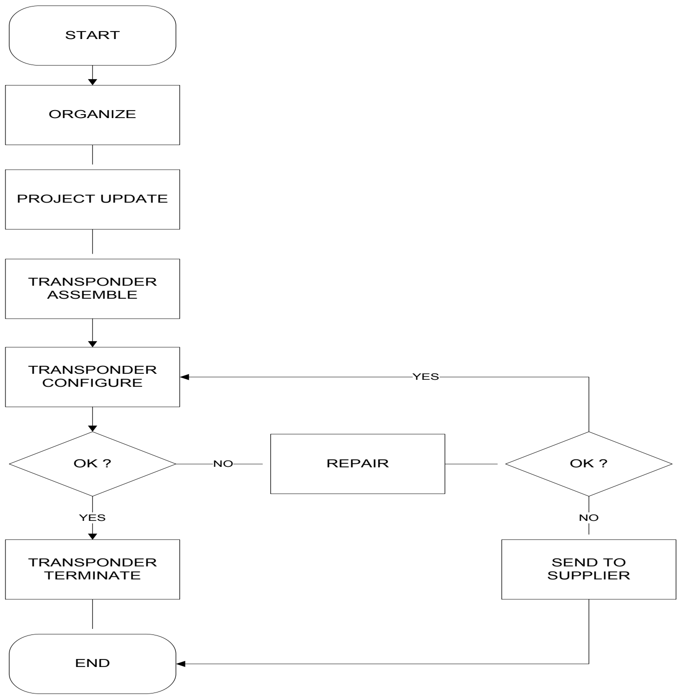


Figure 2: Flowchart of the transponder cell process, the simulation conceptual model

As shown in the flowchart in Figure 2, the cell productive process starts with the organization of the raw material required to a production order. After that, the printed circuit board (PCB) goes through a project update activity, that is, some missing components are assembled on the PCB. Next, the PCB receives the transponder components and it can be configured. If the configuration outcome is positive, then the transponder will follow to the finishing activity. If not, it will be repaired. Even so, the problem is not solved, the PCB is sent to its supplier.

Two operators work in this cell obeying a unique shift. They are able to do every activity inside the cell.

After the construction of this conceptual model, the production times spent for each activity of the flowchart were measured with a stopwatch. These data were statistically treated. As a result, the simulation computational model was fed by the probability distribution of each sample.

It points out here that the conceptual model allowed the process specialists to identify an activity (project update) that should not exist inside the production process, since this activity does not add value to transponders. Actually, this activity is a function of the product development department. Then, this possibility (to eliminate this activity from production process) will be tested as a factor in DOE.

This initial phase of the project took approximately three months and basically it contemplated the understanding of the real system, the conceptual model construction and the data collect.

3.2 Implementation

From now on, the conceptual model is going to be translated into a computational model using the simulator Promodel® from Promodel Corporation, one of the most widely used simulation softwares in the market (Doloi and Jafari 2003). Similarly, some works like Verma, Gibbs, and Gilgan (2000) justify the use of Promodel® due to the possibility of analyzing the simulation by means of graphical animation and by the application and interpretation being easier.

Approximately twelve models were built, according to the complexity increasing. This way, the model verification process occurred as follows: the model was built in steps and only after the modeler´s confirmation (that the model was functioning properly in each step), new increments were incorporated. This procedure was adopted until the final version was finalized. Besides that, deterministic values were initially simulated, in order to certify that the logic of the model was correct. The debugger tool from Promodel® software was also used, which pointed out programming errors.

Moreover, the testing runs were performed with the enabled animation option. This function allowed the researchers to verify inconsistencies in production flow and even the undesired effect of the simulation transitory phase. Counters were also inserted along the model for local result measurement. This way, some mistakes could be found.

Then, the last computational model was submitted to the validation process. Figure 3 shows the final screen of the simulation animation.

Firstly, face to face validation (Kleijnen 1995; Sargent 1998) was executed, where the model was presented to the current system users. By means of graphical animation the specialists were able to evaluate the system behavior. In this test, the computational model was validated.

After that, statistical tests (hypothesis tests and Normality test) were performed under the production quantity a week to assure the validity of the simulation model using the software Minitab®. For this, the model was executed for eighteen weeks, with ten replications each one. The production quantity was obtained from the average of the values of ten replications. At the same time, historical production quantities from the company's ERP system were collected during the same period of time.

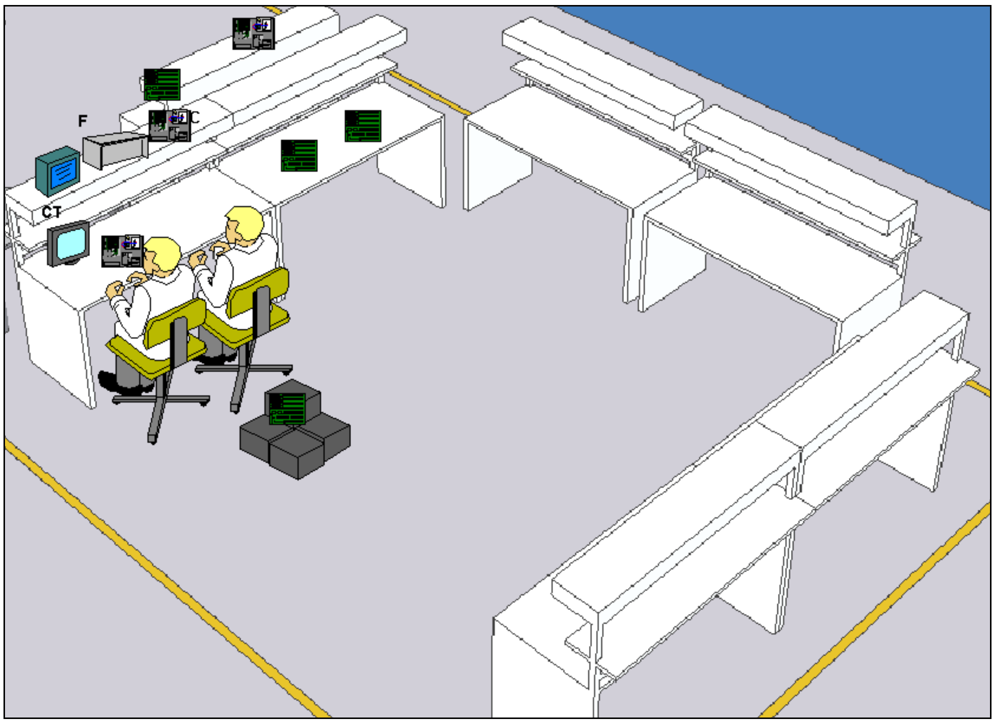


Figure 3: Simulation model of the real system

In possession of these data from simulation model and company's historical production, the data suffered a transformation (square root of the data) to stabilization of the variance. As presented by Bisgaard e Fuller (1994), this procedure is recommended when the simulation model works with a discrete variable (quantity of parts produced per week).

Next, a Normality test was executed for model data and historical data. Through these tests it was verified that these data could be fitted as a Normal distribution. This fact eliminates the use of nonparametric statistic in the next tests. After that, the f test was executed (used to perform hypothesis tests for equality or homogeneity of variance between two populations).

Through this test it was verified that the two data sets (real and simulated) do not have equal variances. This information does not invalidate the model, but give orientation to choose the final test for means (Two Sample t).

Two Sample t test will show the acceptance of the model as a good representation of the real system or not. This test is used to perform a hypothesis test and compute a confidence interval of the difference between two population means when the population standard deviations are unknown. As the result of this test, the differences between output of the model and output of the real system are not statistically significant, considering 95% of confidence level.

Then, after this validation process (face to face and statistical tests) we assured that the simulation model developed was validated. In other words, the computational model of simulation is capable of receiving experimentation.

This second phase of our work was performed for two months and regarded the building, verification and validation of the simulation model.

3.3 Analysis

This phase was the most expected by the simulation team and managers, because it contains the results obtained from insights under the real system. By using a simulation model, these insights can be tested before being implemented in the real system. As already discussed in item 2, these tests were performed through a suitable methodology that is the Design of Simulation Experiments. The experimental matrix used was 2^k type. Where, k is the quantity of factors.

According to Sanchez, Moeeni, and Sanchez (2006), many studies related to operation management use the full factorial experimental designs because of their simplicity, and because they allow the analyst to identify interactions among the factors as well as main effects.

The disadvantage of using full factorial lies on the amount of time and experiments needed to be spent. According to Kelton (1999), when the number of factors becomes moderately large, the number of experiments explodes. A possible solution for this situation is the use of fractional factorial, in which only a fraction of all possible combinations are evaluated. This solution is indicated when there is a great number of factors to be analyzed and only the main effects of the factors are considered important.

The simulation team and the process specialists defined the interest in evaluate the main effect of six factors under the quantity of transponders produced a month. In Table 1, these factors are shown with their levels.

Table 1: Description of the six factors and their levels

Symbol	Factors	Low level	High level
A	Quantity of workbench without equipment	1	3
B	Quantity of operators for shift	2	5
C	Quantity of workbench with equipment	1	3
D	Organization activity performed by operators of the cell	yes	no
E	Project update activity present in the process	yes	no
F	Quantity of shifts	1	2

By considering six factors, with two levels each one, it has an amount to sixty four simulated experiments (sixty four scenarios). And they were executed with ten replicates each experiment. The statistical analysis was done using Minitab®, a statistical software.

The execution of the experiments without simulation models is frequently expensive or even impracticable. For this reason, the use of simulated experiments is recommended, and the results of this integration between design of experiments and simulation is presented as follows.

Firstly, as showed in Table 2, the six-way interactions and the five-way interactions can be discarded, once their *P-Values* are greater than 0.05 (significance level).

The analysis of the main effects of each factor, presented in Figure 4, shows that factor B (quantity of operators for shift) has a strong positive effect over the final response, that is, the amount produced. This means that the alteration of the low level to the high level increases the final production.

Table 2: Analysis of Variance for monthly output

Source of Variation	*Degrees of Freedom*	*Sum of Squares*	*Mean Square*	*Fo*	*P-Value*
Main Effects	6	58118912	9686485	56874.68	0.000
2-Way Interactions	15	6215291	414353	2432.89	0.000
3-Way Interactions	20	988355	49418	290.16	0.000
4-Way Interactions	15	70780	4719	27.71	0.000
5-Way Interactions	6	2142	357	2.1	0.052
6-Way Interactions	1	158	158	0.93	0.335
Residual Error	562	95716	170		
Total	625	65279256			

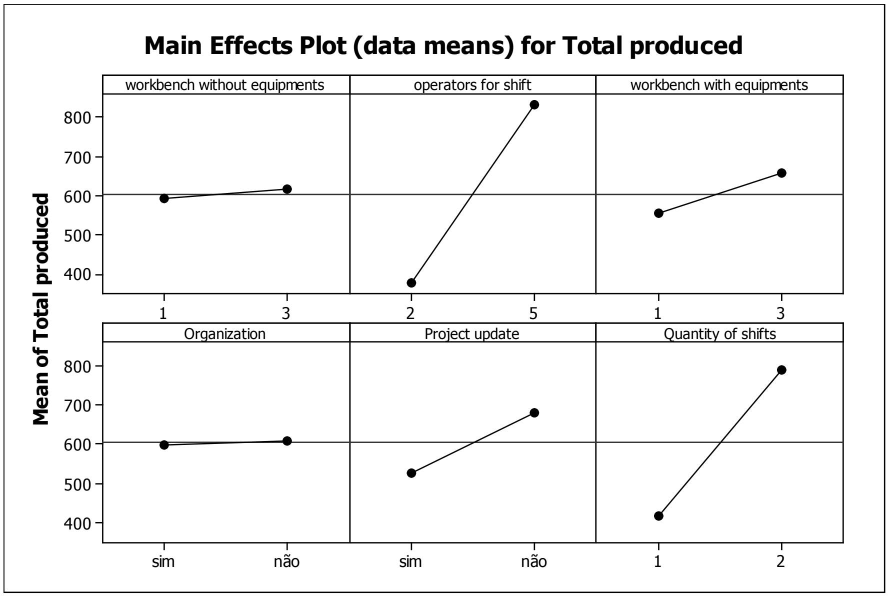


Figure 4: Graph of the main effects

The weight of the main effects can be noticed in the Pareto chart, shown in Figure 5. On this figure, it can be verified that all the factors and their interactions are significant for a 95% of degree of confidence.

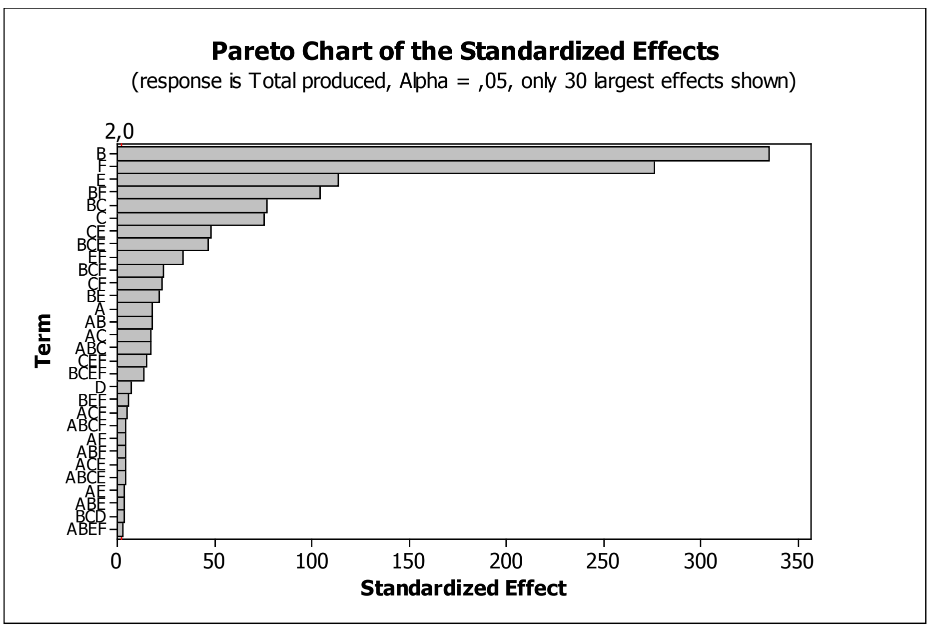


Figure 5: Pareto chart of the standardized effects

The occurrence of interaction with significant effects (BF, BC e CE) imposes the necessity of analyzing the interactions. The interactions of second order are shown on Figure 6, and it is possible to confirm the interaction among these factors.

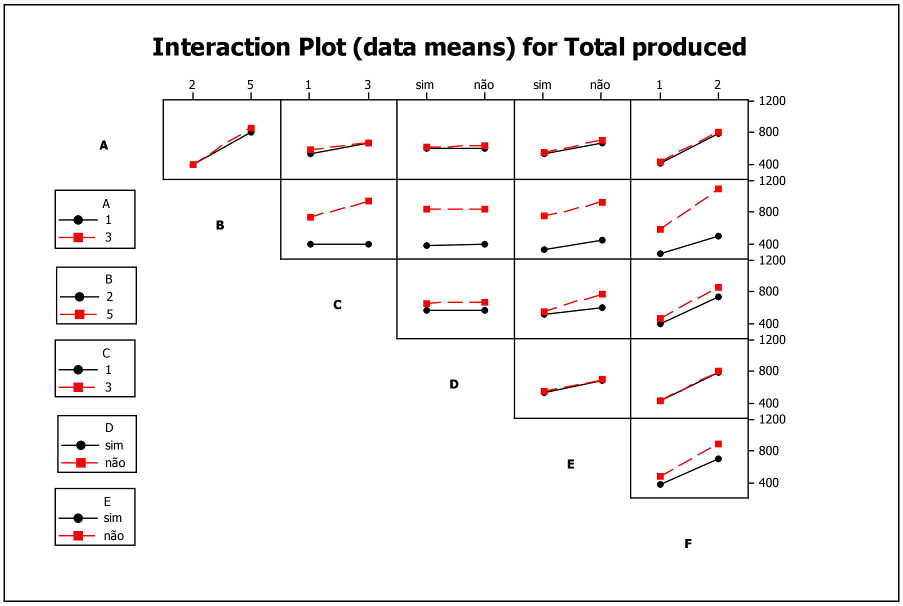


Figure 6: Second order interaction between the factors

Montgomery (2005) affirms that an adequately formulated model must present uncorrelated normally distributed residues. It is understood by model residue (or model error) the difference between an observation and its estimated value (or adjusted) from a statistical model.

This way, the residues were submitted to a normality test in the software Minitab®. Besides that, it was also verified the possibility of existing any residue tendency. The tests were favorable.

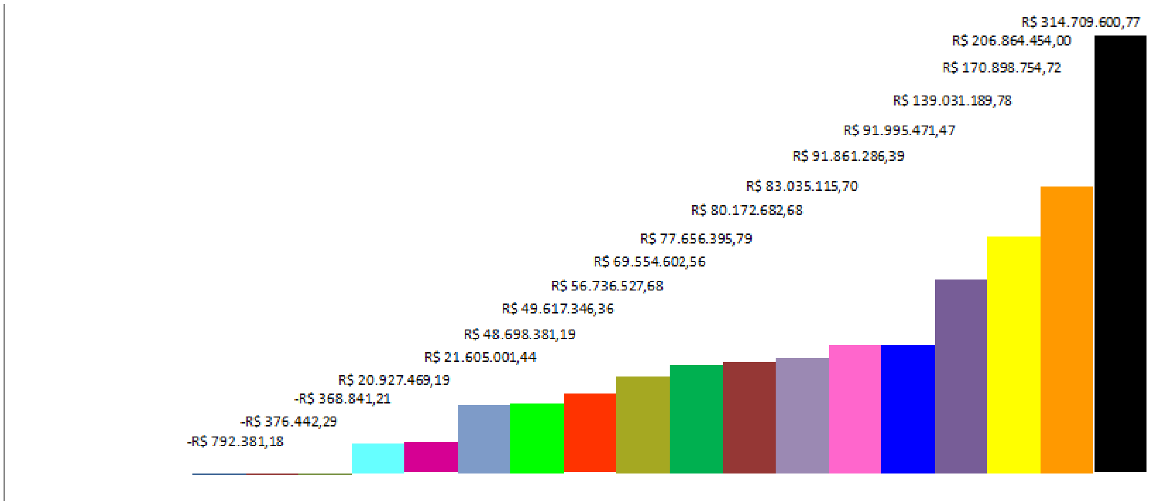
After the DOE analysis, it becomes important to evaluate which scenario is the best to the company under the economic point of view. The question to be answered in this analysis is: Is the revenue produced by the increment in the total produced because of the change of a low level to a higher level (DOE) bigger than the costs and the investments required to realize that scenario?

In order to answer this question, it was used the Net Present Value (NPV) criterion. It points out here a great contribution of DOE to elect the relevant scenarios to be economically evaluated rather than evaluate all of them.

Pareto chart, presented in Figure 5, shows that eighteen scenarios are more significant among the sixty four scenarios tested. Then, to each one of these eighteen scenarios, a cash flow was built.

This cash flow was analyzed for twelve months. The interest rate was considered as 1,46% a month. The revenues were calculated by the product of the total produced by the scenario (output from simulation model) and contribution margin. The costs and the investment depend on each scenario. There are scenarios that do not consider investments (for example, to buy a piece of equipment), but there are costs produced by the increasing of operators (wages) or by the increasing of shifts (costs with electric power, nocturnal additional, alimentation, transportation, materials, depreciation of equipment).

In face of these data, the deterministic NPV of each scenario was calculated. Figure 7 shows a graph that classifies the scenarios by the respective NPV´s increasing order. This figure shows the increment in the output (monthly) that each scenario generate, too.



SCENARIO	13	15	6	3	7	11	2	1	12	14	5	16	17	9	8	4	10	18
A	0	2	2	0	2	2	0	0	0	0	2	2	2	0	2	0	2	2
B	0	0	0	0	0	0	0	3	3	3	3	3	0	0	3	3	3	3
C	2	2	0	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0
F	0	0	0	0	0	1	1	0	0	0	0	0	1	1	0	1	1	1
INCREMENT IN OUTPUT	-3	-1	-1	80	83	189	192	217	266	297	307	318	354	354	532	656	794	1206

Figure 7: Classifications of the scenarios by the respective NPV´s increasing order

This graph supports the decision makers with options based on data to aid in the process of making a decision. In the lower border of this graph, it is shown the variables considered in the economic analysis, with their respective values of each scenario. For example, the scenario 03 does not consider any new investment, since it considers an improvement in the time of the project update activity. This improvement generates an increment of eighty transponders monthly and it results in a NPV in the order of twenty millions Reais (approximately US$ 8.800.000,00). In the same way, the other scenarios can be analyzed.

When the simulation team presented this result to the decision makers, they were sure that the scenario 03 has been applied in the transponder production cell. This procedure was used to verify if the forecasted results by the simulation model would be confirmed in the real world. It is known in simulation as the credibility step.

Credibility is when a simulation model and its results are accepted as "correct" by the decision maker (or manager) and other key project personnel. Validity does not imply credibility and vice versa. For example, a valid or technically correct model might not be used in the decision making process if the model's key assumptions are not understood and agreed with by the decision maker. Conversely, a credible model based on an impressive three dimensional animation might not be technically sound, Law (2005).

The simulation model presented in this paper got credibility by the decision makers. The results reached in practice were favorable and near the results forecasted by the simulation model.

Still analyzing Figure 7, it can be perceived that fifteen scenarios are economically attractive (NPV is higher than zero). And three scenarios are not economically feasible (NPV is less than zero).

From the economic view point, the best scenario is number 18, because the NPV is the highest. However, the company cannot have the demand to support the scenario production. So, the decision makers can know the NPV of a scenario that attends a forecasted demand for transponder.

Another analysis that can also be made is the comparison among scenarios. For example, if the company wants to increase the output monthly, but it does not want to have a new shift, in that case the best scenario is number 08. This one is economically better than many scenarios that have shift (2, 11, 17 e 9).

By looking at the graph, it is more economically feasible to hire three more operators (scenario 01) than only buying new pieces of equipment (scenario 07).

When dealing with an industrial investment there are variability and risks. So, the contribution margin can vary according to the client. The total produced in a month and the cost associated with that can also vary along the time. Unlike the deterministic analysis where mean values of variables are considered, in the random analysis the variables obey a probability distribution.

In doing so, to know the risk of an investment to be unfeasible, in other words, by knowing the probability of the NPV of each scenario to be less than zero is an important information before performing any industrial investment.

All things being considered, it was performed a Monte Carlo simulation, via Excel® and Crystal Ball®. Three input variables were considered with their respective probability distributions: contribution margin, costs and total produced monthly. The output variable is the NPV, that is, the desirable probability distribution.

Figure 8 shows the risk of choosing scenario 06, that is, only buying one more workbench with pieces of equipment. This risk is 56%. It means that, there is 56% of chance of the NPV to be less than zero. In the same way, the other scenarios can be analyzed.

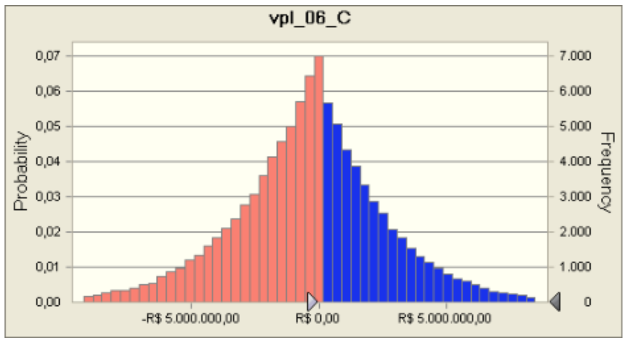


Figure 8: Risk associated with scenario 06

This last phase of the project took three months and contemplated the execution of the experiments, documentation and presentation to the decision makers.

4. CONCLUSIONS

Therefore, the main contribution of this research is the use of the computational simulation methodology to economically evaluate industrial scenarios and to know the economic risk associated with them. In particular, the total produced by the simulation model was used as an input for the Monte Carlo simulation, in face of using values based just on the experience of a specialist or arbitrary data.

The results to Padtec started in the conception phase, where the entire process was documented through mapping and modeling techniques as SIPOC, IDEF0 and Flowchart. These techniques formed the simulation conceptual model.

This conceptual model allowed the process specialists to identify an activity (project update) that should not exist inside the production process. This possibility was tested as a factor in DOE. It points out as a third more significant effect on the total produced monthly. Padtec applied this scenario and the results were near the simulation results. The simulation model has credibility among the decision makers.

Besides that, sixty four scenarios were simulated, with ten replicates each one. This fact shows the power of simulation. Without simulation it would be expensive and even impossible to perform all these scenarios in practice.

DOE was used to elect the most relevant scenarios to be economically evaluated. In doing so, the simulation team was able to save time.

Finally, the scenarios chosen by DOE were analyzed under the economic point of view. Questions like “Are the revenues produced by the increasing of the output higher than costs and investments?” were answered through the Net Present Value of each scenario. It enables the decision makers to compare the alternatives according to the forecasted demand.

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