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Economic Evaluation of Scenarios for Manufacturing Systems Using Discrete Event Simulation Based Experiments

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Abstract

This paper aims to perform economic evaluation of scenarios for manufacturing systems via discrete event simulation based experiments. First, three simulation models were built to mimic three manufacturing cells from two companies. In these simulation models, there are eight, thirty two and sixty four scenarios to be economically analyzed. Then, the decision makers can choose the best scenario by selecting the highest net present value, according to a future predicted demand. The research´s results allowed the identification of an activity that should not exist inside the production process (an analyzed scenario). So, the simulation model gained credibility among the decision makers after it pointed out a 35% of increase in the current monthly output. Finally, this work is concluded by highlighting the role of the design of experiments to select the most relevant scenarios to be economically analyzed. This saves time, when there are a large number of scenarios.

Keywords: *Discrete event simulation, Investment evaluation, Manufacturing systems, Design of experiments, Net Present Value*

Introduction

Computer based simulation has been widely used as a decision support for modeling, analysis, and design of systems to characterize the impact of changing parameters on system performance (Cho, 2005). Additionally, O'Kane *et al*. (2000) state that simulation has become one of the most popular techniques for the analysis of complex problems in manufacturing environments.

We highlight at least three advantages of using discrete event simulation models to perform experiments under economic considerations.

Firstly, the modern manufacturing systems usually present great complexity

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mainly due to its dynamic and random nature. The simulation model can capture these characteristics with more accuracy, attempting to reproduce in a computer the same behavior that the system would show if under equal form conditions (Chwif and Medina, 2007).

Secondly, computational simulation is an appropriate tool for analysis and evaluation of situations that would not be possible in the real world or would be very costly (Shannon, 1998).

Thirdly, simulation is a useful tool to investigate a wide variety of "what if" questions about the real world system. Potential changes to the system can first be simulated, in order to predict their impact on system performance (Banks *et al*., 2005). The same authors state that the model can produce valuable insight into which variables are the most important and into how variables interact.

As consequence of this last advantage, Kleijnen *et al*. (2005) state that many simulation practitioners can get more from their analyses by using the statistical theory on design of experiments specifically developed for exploring computer models. In this research, full factorial designs were adopted. According to Sanchez *et al*. (2006), many operations management studies in the literature use full factorial experimental designs because of their simplicity, and because they allow the analyst to identify interactions among the factors as well as the main effect.

However, Spedding and Sun (1999) consider that simulation results involving increased throughput or production time are not enough for management to make decisions. The same authors also state that 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.

In addition, as referred to in Nazzal *et al*. (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 this, the goal of this paper is to perform an economic evaluation of scenarios for manufacturing systems through discrete event simulation based experiments. To accomplish the objective of this research, three valid simulation models were built. One of them was developed in a manufacturing cell of a multinational automotive plant and the others were developed in a high technology Brazilian company.

There are eight scenarios in the first application while the second has thirty two and in the third application there are sixty four scenarios to be economically analyzed.

Then, the decision maker can choose the best scenario to invest according to a predicted demand. Therefore, an analysis of the alternatives can be conducted by selecting the highest net present value (NPV).

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The comparison of alternative systems is one of the most important uses of simulation (Banks *et al*., 2005). Besides that, according to Coates and Kuhl (2003), as the projects become more complex, simulation provides convenient and powerful means of conducting such analysis.

In its turn, the simulation models can provide the production quantity to enter in the cash flow with more accuracy in comparison to data based only on the experience of a process specialist or on arbitrary data.

Thus, the main contribution of this work is the use of design of experiments to select the most relevant simulated scenarios to be economically analyzed, when there are a lot of scenarios. As a consequence, the analysts will spend less working time on the construction of cash flows and calculation of the NPV's only on the relevant scenarios than they would if they had to do it for all of the scenarios.

The main result of this research is applied today by Padtec S.A., a high technology Brazilian company. In the case of the transponder A cell, this research allowed the identification of an activity that should not exist inside the production process (project updating). So, Padtec has applied a scenario that eliminates this activity and the results from the real system were increase close to the results pointed by simulation. The simulation model gained credibility among the decision makers after it pointed out a 35% of increase in the current monthly output.

We begin by presenting the modeling and simulation research method and a sequence of steps for this simulation study. After, some background information, about the two companies where the research was conducted, is provided. The three simulation models are described, and the full factorial designs performed to indentify the relevant scenarios to be economically analyzed are shown. So, the net present values are presented and the results from the economic analysis are discussed. Finally, the last section contains our concluding remarks.

Research Method

According to Martins (2010), when developing a modeling and simulation method a researcher manipulates the variables and their levels, but it does not in the reality. This is done by using a research model, which is an abstraction of reality. May have or may have not the use of computers to manipulate the model´s variables.

Currently, the modeling and simulation method is one of the most applied methodological approaches in Industrial Engineering and Operations Management, followed by Survey, Case Study and Action Research (Miguel, 2007).

Figure 1 shows an adapted flow chart from Montevechi *et al*. (2007), in which the logic to design simulation experiments is explained. Now, the flow chart was adapted to obtain the net present value of each relevant scenario in a manufacturing system. This sequence is divided into three main phases: conception, implementation and analysis.

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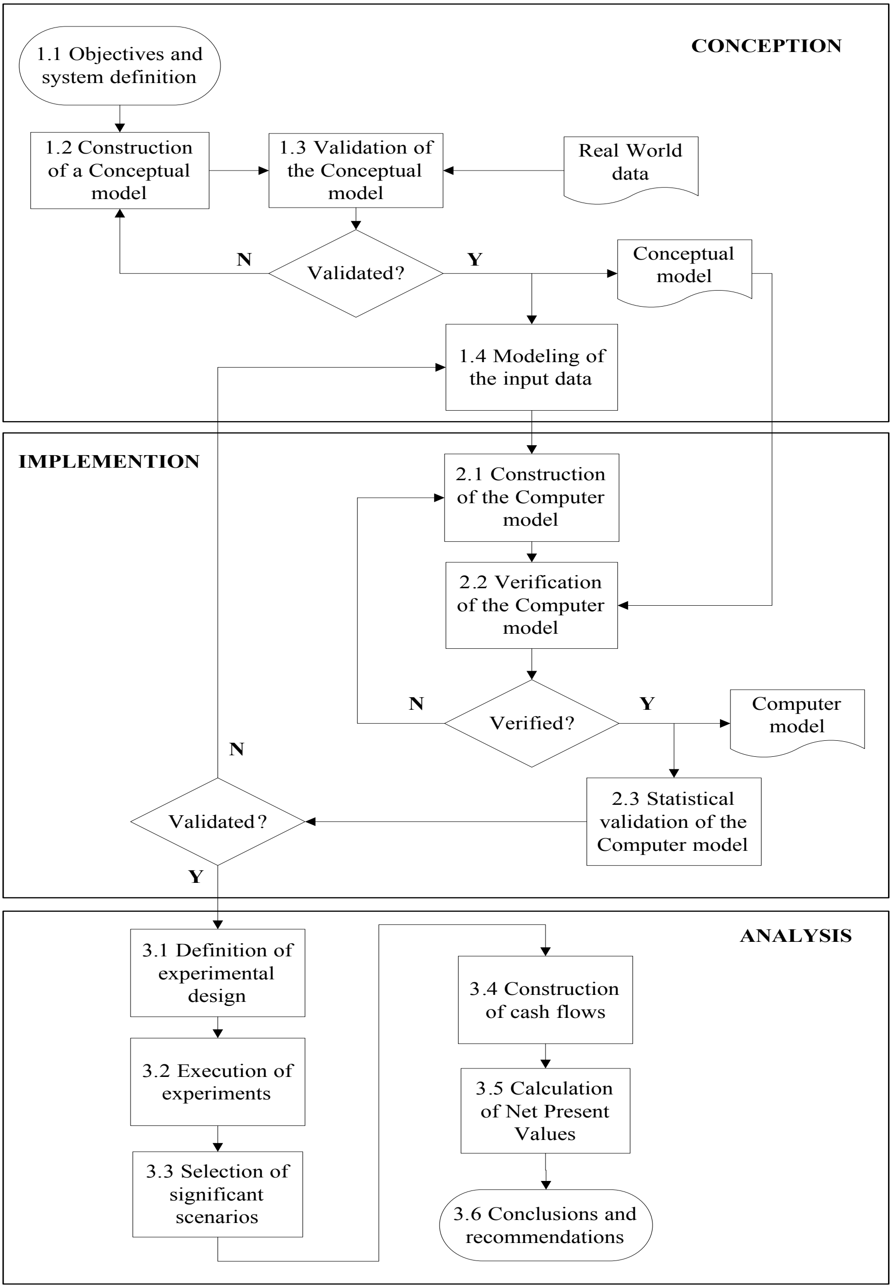

Figure1 - The sequence of steps for this simulation study

Source: adapted from Montevechi *et al*. (2007)

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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, by making the construction of the computational simulation model easier. Some techniques that can be used in this phase are: value stream mapping which is found in Abdulmalek and Rajgopal (2007), process mapping as referred to in Greasley (2006), flow chart, SIPOC (Suppliers Inputs Process Outputs Customers), IDEF0 (Integrated Definition methods language 0) 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 (independent) and the output variables (dependent) 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. In this paper, Promodel® simulator was used to build and run models. 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.

The simulation models in this paper were verified using several techniques discussed in Banks *et al*. (2005), such as enabling the simulation animation to verify that what is seen in the animation imitates the actual system. To validate the simulation models methods such as the ones discussed in Sargent (2004) were used. These include comparing the simulation outputs against the system's outputs through hypothesis tests and face validity.

Lastly, but not less important, the analysis phase. Once the model was verified and validated, it is time to experiment inside the domain of validation. This phase is the most expected by the project team. Sanchez (2007) states 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 analyst. One extremely effective way of accomplishing this is to use design of experiments (DOE) to help explore the simulation model.

In simulation, the use of DOE has shown great impact in decision making support. Kelton (1999) states that the 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. 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).

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DOE combined with simulation models has been used successfully in many works in the literature. Works such as Nazzal *et al*. (2006), Meade *et al*. (2006) and Ekren *et al*. (2010) have recently used experimental designs to identify the significant variables in a simulation model.

Nazzal *et al*. (2006) used fractional factorial design, hypothesis tests and characteristics curves to help calculate the net present value for the cost of cycle time reduction resulting from the additional tools in a station family of a production line simulation model.

In addition, Meade *et al*. (2006) performed a general factorial design in the lean manufacturing context to test the influence of accounting methods, inventory policies and sales volume on the net profit.

Moreover, Ekren *et al*. (2010) performed a simulation based experimental design to identify the factors that could affect the response measures for an automated unit load, storage and retrieval systems in France. In that paper, the authors noted that the cost of making changes in those factors (number of lifts and vehicles) should also be considered.

In order to improve the decision making process, by giving the managers the NPV of each relevant scenario to expand the production capacity, discrete event simulation models were built to imitate real manufacturing cells. After that, full factorial designs were performed to select only the significant scenarios to be economically analyzed through the NPV technique.

The sequence of steps shown in Figure 1 was followed to each of the three objects of study. However, for the sake of simplicity, the complete steps are presented here just to one of them, the simulation model for transponder A. It is Padtec's strategic product, therefore it is interesting to study its manufacturing process.

Backgrounds

This section provides some background information about the two companies where the research was conducted.

A High Technology Brazilian Company

Since 2001, Padtec has been a high technology Brazilian company that assembles pieces of equipment which form Wavelength Division Multiplexing optical systems. Two manufacturing cells (objects of study) were chosen. One cell assembles transponder *A* and the other transponder *B*. They represent almost 40% of the company´s revenue, while the second product of major revenue corresponds to 20%.

To begin with the conception phase, a SIPOC diagram, an IDEF0 and a flow chart were built and they were presented in Montevechi *et al*. (2008), in an effort to improve the understanding of the productive process of each cell.

The flow chart for transponder *A* is presented in Figure 2 and it constitutes

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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. This is the face validation (Sargent, 2004), that aims to validate the logic in the conceptual model and to assure that the inputs and outputs are reasonable. Therefore, the simulation conceptual model was validated.

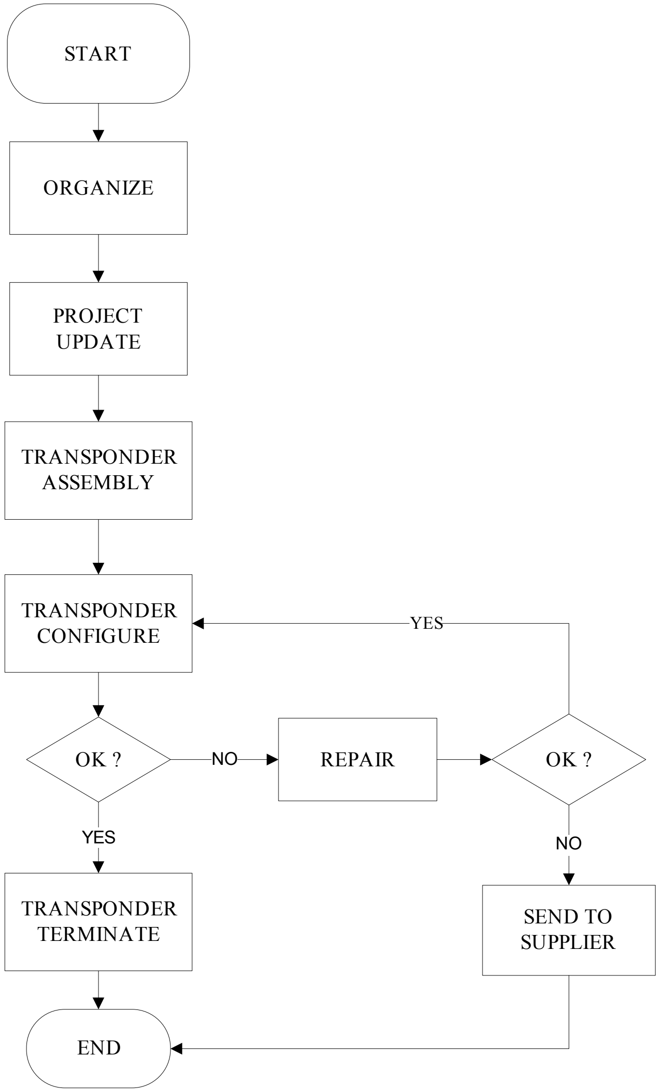

Figure 2 - Flow chart of the transponder A process, the simulation conceptual model

As shown in the flow chart in Figure 2, the productive process of the cell starts with the organization of the raw material required for a production order. After

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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, if the problem is not solved, the PCB is sent to its supplier.

Two operators work in this cell obeying a unique work 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 flow chart 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 is important to point out at this stage 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 the 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 analysis.

Similarly to transponder *A*, the conception phase for the assembly of transponder *B* was developed.

A Multinational Automotive Plant

Regarding the conception phase for the multinational automotive plant, the application of the simulation method in that cell was motivated by two reasons. Firstly, because of an environmental cause, the current degreaser needed to be replaced by another, less aggressive to the environmental one. Secondly, because of the implementation of the Lean manufacturing system, that demanded the adoption of the continued flow.

To accomplish these goals the manager could change three factors in two levels each one, therefore there are eight simulated experiments or scenarios which observe these premises. These scenarios were built on the simulation model that mimics the current system.

This current system is a manufacturing cell that changes the raw material into partially finished goods. After the first operation of milling, the parts are inspected by sampling, then these parts are taken by the operators to the degrease machine and after that they can be treated in an electric furnace.

Nowadays there are nine available machines (four machines type A, four machines type B and one machine type C) and two electric furnaces. There are two operators per work shift (three shifts in all), who command and set up two machines each one. They have to inspect and move the parts over the process. In addition, there is one operator per work shift, who is responsible to load and command the electric furnaces.

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This way, a conceptual simulation model was developed to imitate the logic of the real system and it was validated.

Simulation Modeling of the Systems

Simulation Model to the Transponder A Cell

In the implementation phase, the conceptual model shown in Figure 2 was translated into a computational model by using the simulator Promodel®, which is a simulation and animation tool designed to model manufacturing systems.

Approximately twelve models were built, in order of increasing complexity. 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® was also used, which pointed out programming errors, when they appeared.

Moreover, the testing runs were performed with the animation option enabled. 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.

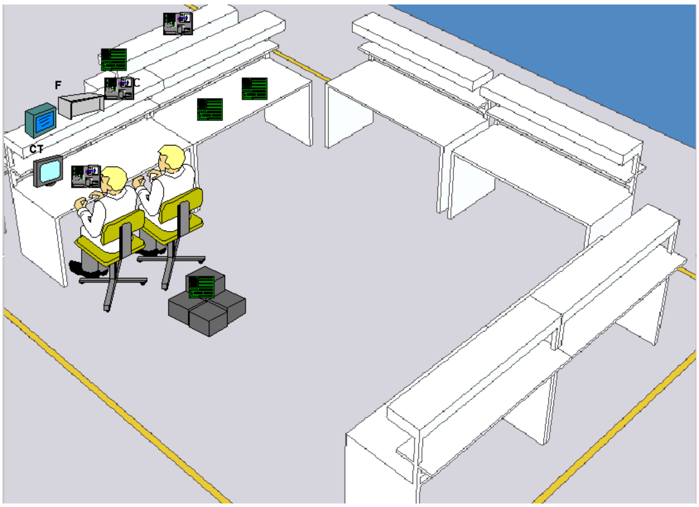

Figure 3 - Simulation model for the transponder A manufacturing cell

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The validation was performed as follows. Firstly, a face validation (Sargent, 2004) was executed. In this procedure, 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 assembled per week to assure the validity of the simulation model using the software Minitab®. In order to do this, the model was executed for eighteen weeks and was run for 10 independent replications. The production quantity was obtained from the average of the values of 10 replications. At the same time, historical production quantities were collected during the same period of time.

In possession of these data from the simulation model and the company's historical production, 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. After that, the test *f* 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 gives 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.

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

Simulation Model to the Transponder B Cell

In the same way, the simulation model to the transponder *B* cell was developed, verified and statistically validated. Figure 4 shows a screen of this model.

Multinational Automotive Plant

This model was programmed in two modules to facilitate the verification process, according to Sargent (2004). Figure 5 brings a screen of the final simulation model.

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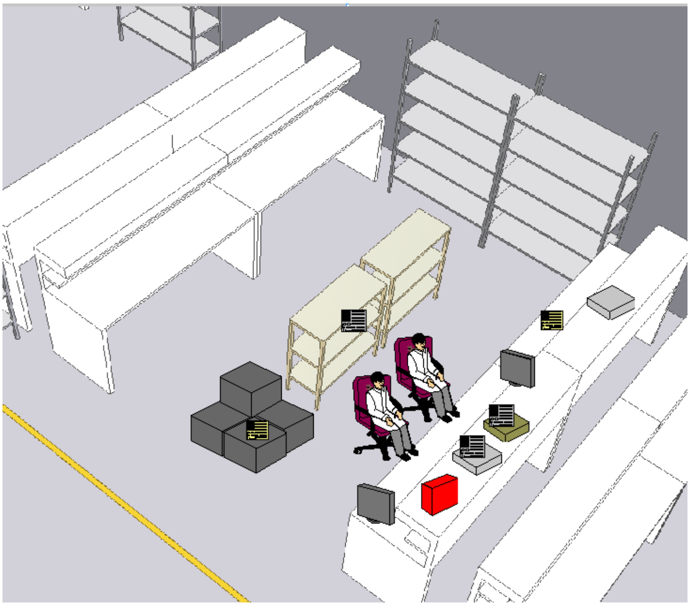

Figure 4 - Simulation model for the transponder B manufacturing cell

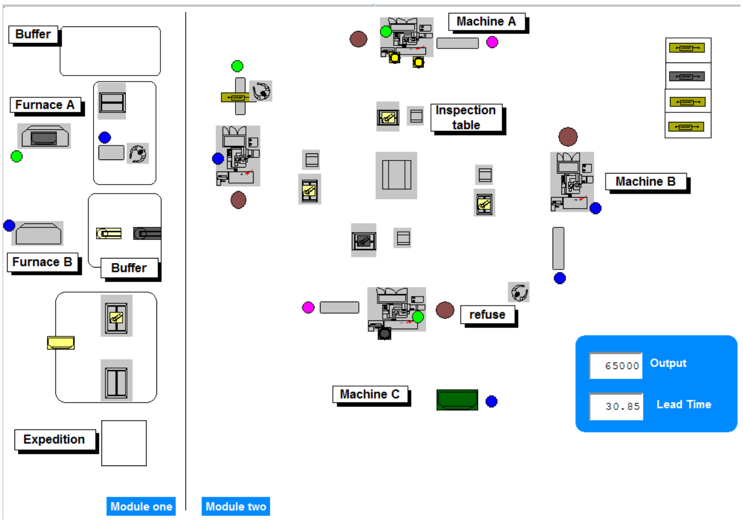

Figure 5 - Simulation model for the automotive plant manufacturing cell

Similarly to the other presented applications, this simulation model was verified and validated.

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Experimental Designs

This experimentation phase contains the results obtained by testing 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 section 2, these tests were performed through a suitable method that is the design of simulation experiments. The experimental matrix was a 2^k type, where, k is the quantity of factors. The statistical analysis of DOE was done using Minitab® statistical software.

Factorial designs are the only way to find factor interactions avoiding incorrect conclusions when factors interactions are presented (Montgomery, 2005).

The disadvantage of using full factorial lies on the amount of time needed to be spent and experiments to be done. 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 large number of factors to be analyzed and only the main effects of the factors are considered important.

In order of increasing complexity, this section begins the analysis phase with the automotive manufacturing cell because there are only eight scenarios to be economically analyzed while the transponder *B* manufacturing cell has thirty two and the transponder *A* has sixty four scenarios.

Multinational Automotive Plant

The production manager could change only three factors in two levels each one. Therefore, there are eight experiments. Each experiment was called a scenario, which is a combination of these three factors. Table 1 brings the description of the three factors and their levels.

Table 1 - Description of the three factors and their levels

Symbol	Factors	Low level	High level
A	Quantity of operators in module one	2	4
B	Quantity of shifts in module two	3	2
C	Quantity of automatic machines	0	4

Then, eight simulation models were built to represent these scenarios. All of them observe the replacement of the current degrease machine for a new machine that operates between machines A and B by generating the continued flow among the cell operations. However they are different from each other in terms of the number of operators in module one, number of work shifts in module two and number of automatic machines in module two.

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Figure 6 illustrates the Pareto Chart of the factor effects on the monthly output. By examining the magnitude and direction of the factor effects it is possible to determine which variables are likely to be important (Montgomery, 2005). The analysis of variance (ANOVA) can be used to confirm this interpretation, Table 2 shows this ANOVA.

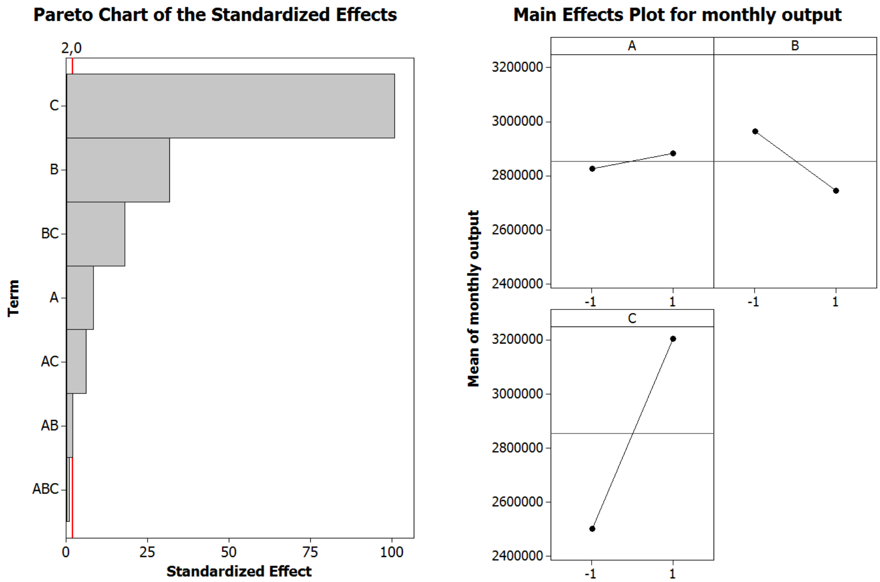

Figure 6 - Pareto chart and Main effects plot for monthly parts production

Table 2 - Analysis of Variance for monthly parts production

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Square	F	P-Value
A	1	3.3E+10	3.34E+10	68.28	0.000
B	1	4.8E+11	4.85E+11	990.70	0.000
C	1	4.9E+12	4.95E+12	10,111.11	0.000
AB	1	1.5E+09	1.52E+09	3.11	0.087
AC	1	1.7E+10	1.78E+10	36.42	0.000
BC	1	1.5E+11	1.57E+11	321.11	0.000
ABC	1	342,225,000	3.4E+08	0.70	0.410
Residual Error	32	1.5E+10	4.9E+08		
Total	39	5.6E+12			

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This way, only five out of eight scenarios tested are significant for a 95% of degree of confidence. Additionally, the three main factors are significant and only the two ways interactions BC and AC are important.

Figure 6 also brings the main effects plot for the monthly output. This means that factor C (quantity of automatic machines) has a strong positive effect on the monthly output. As factor B (quantity of work shifts in module two) has a negative effect on the monthly output, this suggests that changing B from the low level (three work shifts) to the high level (two work shifts) will decrease the monthly output.

In this case, all main factors are significant, however in other situations non significant factors can exist, that do not need to be economically analyzed.

After the DOE analysis, it becomes important to evaluate which scenario is the best for the company from the economic point of view. The question to be answered in this analysis is: Is the revenue generated by the increment in the total produced because of the change of a low level to a high level (DOE) higher than the costs and the investments required to realize that scenario? In order to answer this question, the Net Present Value (NPV) criterion was used.

Then, for each one of these five significant scenarios a cash flow was built. This cash flow was analyzed over five years. The interest rate was considered as 10% a year. The revenues were calculated as the product of the increment in total produced by the scenario (output from simulation model) and unit contribution margin. This way, it has been analyzed if the annual increment on the output by a scenario in comparison to the current system output economically justifies the investment in this scenario.

The costs and the investment depend on each scenario. There are scenarios that consider investment in automatic machines and there are costs produced by the increase in the quantity of operators (wages) or by the increase of shifts (costs with electric power, night shift salary differential, food, transportation, materials, depreciation of equipment). The data was coded because of the industrial confidentiality.

Simulation Model to the Transponder B Cell

In this object of study, the objective of the simulation team and the process specialists was to test scenarios to expand the production capacity by changing five factors in two levels each one. So, this adds up to an amount of thirty two scenarios and they were executed with ten replicates each one. In Table 3, these factors are shown along with their levels.

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Table 3 - Description of the five factors and their levels

Symbol	Factors	Low level	High level
A	Quantity of workbench without equipment	1	2
B	Quantity of operators for shift	2	4
C	Quantity of workbench with equipment	1	2
D	Organization activity performed by operators of the cell	yes	no
E	Quantity of shifts	1	2

The effect magnitude of each factor can be visualized at the Pareto Chart in Figure 7. By analyzing this figure and the ANOVA shown in Table 4 it can be observed that only eleven out of the thirty two scenarios analyzed are significant for the monthly output.

As a matter of fact three out of the five main factors are among these significant eleven. This can also be visualized at the main effects plot in Figure 7. From this analysis, it can be concluded that the main factors A (quantity of workbench without equipment) and D (organization activity performed by operators of the cell) do not have significant effects on the monthly production of transponder B.

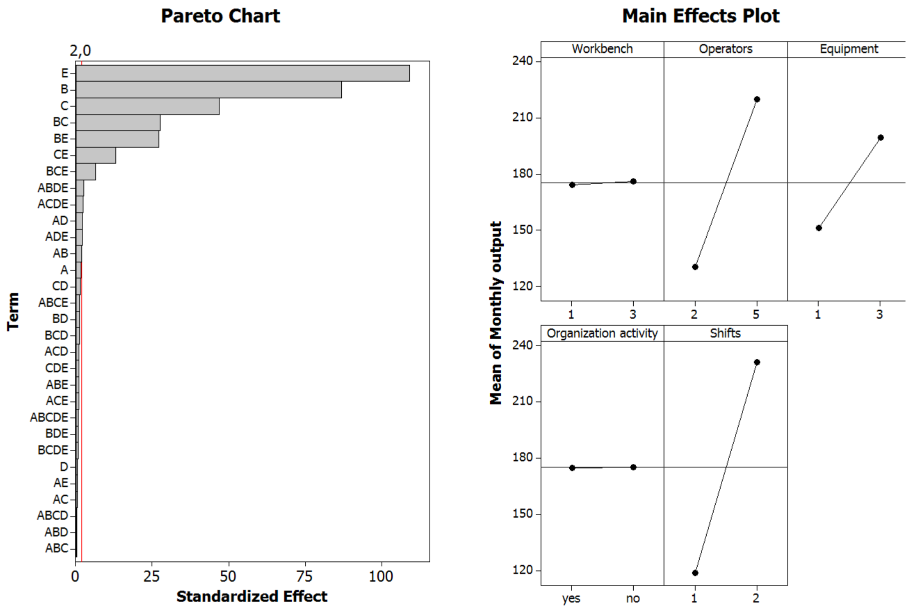

Figure 7 - Pareto Chart and main effects plot for monthly transponder B production

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Table 4 - Analysis of Variance for monthly production of transponder B

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Square	F	P-Value
Main Effects	5	1,844,024	368,805	4325.2	0.000
2-Way Interactions	10	142,14	14,214	166.7	0.000
3-Way Interactions	10	4,206	421	4.93	0.000
4-Way Interactions	5	1,165	233	2.73	0.020
5-Way Interactions	1	47	47	0.55	0.461
Residual Error	288	24,557	85		
Total	319	2,016,139			

The great contribution of DOE to elect eleven scenarios which are relevant to be economically evaluated is highlighted here, rather than evaluating all of the thirty two.

Then, for each one of these eleven scenarios, a cash flow was built. This cash flow was analyzed for twelve months. The interest rate considered was 1.46% a month. The revenues were calculated as the product of the total produced by the scenario (output from simulation model) and the contribution margin. The costs and the investment depend on each scenario. There are scenarios that do not consider investments (for example, buying a piece of equipment), but there are costs produced by the increase of operators (wages) or by the increase of shifts (costs with electric power, night shift salary differential, food, transportation, materials, depreciation of equipment).

Simulation Model to the Transponder A Cell

At last, for transponder *A,* the simulation team and the process specialists demonstrated interest in evaluating the main effect of six factors under the quantity of transponders A produced a month. In Table 5, these factors are shown with their levels.

Table 5 - 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

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By considering six factors, with two levels each one, there is an amount for sixty four simulated experiments. Similarly, each experiment was called a scenario which is a combination of these six factors. And they were executed with ten replicates each one.

The execution of the experiments like this 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, based on the analysis of variance shown in Table 6, the six-way interactions and the five-way interactions can be discarded, once their P-Values are greater than 0.05 (significance level).

Table 6 - Analysis of Variance for monthly production of transponder A

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Square	F	P-Value
Main Effects	6	58,118,912	9,686,485	56,874.68	0.000
2-Way Interactions	15	6,215,291	414,353	2,432.89	0.000
3-Way Interactions	20	988,355	49,418	290.16	0.000
4-Way Interactions	15	70,78	4,719	27.71	0.000
5-Way Interactions	6	2,142	357	2.1	0.052
6-Way Interactions	1	158	158	0.93	0.335
Residual Error	562	95,716	170		
Total	625	65,279,256			

The weight of the main effects can be noticed at the Pareto chart, shown in Figure 8. In this figure, it can be verified that all the main factors and some of their interactions are significant.

As the DOE analysis showed that thirty eight out of the sixty four scenarios are significant, Padtec's decision makers decided to economically evaluate only the eighteen most significant scenarios among the thirty eight significant.

Then, for each one of these eighteen scenarios, a cash flow was built. This cash flow was analyzed for twelve months. The interest rate considered was 1.46% a month. The revenues were calculated as the product of the total produced by the scenario (output from simulation model) and the contribution margin. The costs and the investment depend on each scenario. There are scenarios that do not consider investments (for example, buying a piece of equipment), but there are costs produced by the increase of operators (wages) or by the increase of shifts (costs with electric power, night shift salary differential, food, transportation, materials, depreciation of equipment).

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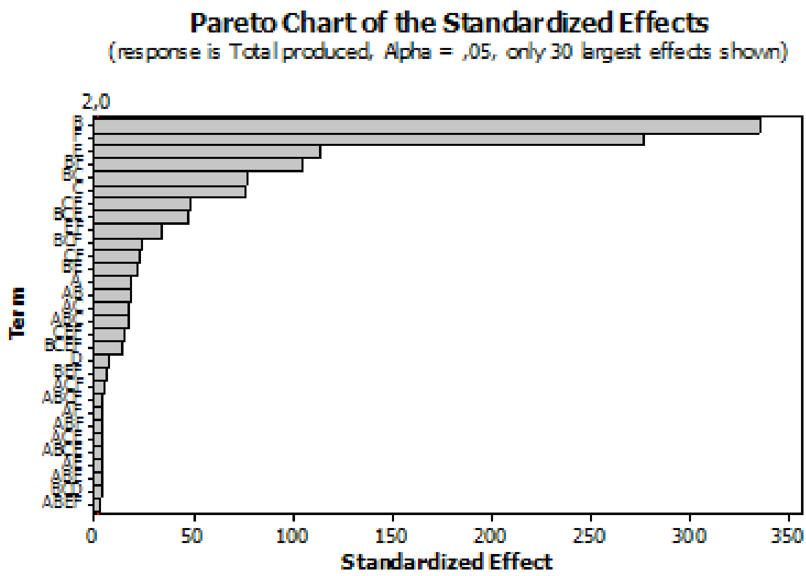

Figure 8 - Pareto chart of the standardized effects

Results and Discussions

From now on, each relevant scenario (pointed out by the DOE analysis) is going to be evaluated under the economic point of view. It is done through the deterministic Net Present Value (NPV) technique. From this analysis, the best scenario for the company can be determined.

Firstly, the automotive manufacturing cell is analyzed. Figure 9 shows a graph that classifies the five scenarios according to their respective NPV´s in increasing order. This figure also shows the increment in the monthly output that each scenario generates.

This graph supports the decision makers with options based on data to aid the process of making a decision. In the lower border of this graph, the variables considered in the DOE and the economic analysis, with their respective values of each scenario is shown. For example, scenario A considers only hiring two more operators per work shift in module one, which means an increment in production of only 106,600 parts monthly, by resulting in a negative NPV in the order of seven thousands Reais (Brazilian currency) (approximately US$ - 3,723). This means that the increment in output does not justify two more operators, the costs associated with this are higher than the created revenues.

By analyzing scenario B, pointed out by DOE as significant because if the company changes from the current three work shifts to only two shifts in the second

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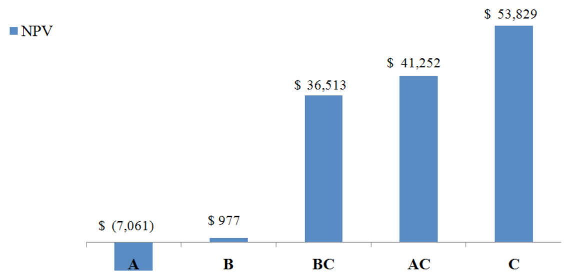

Operators for work shift	2	0	0	2	0
Work shifts	0	-1	-1	1	1
Automatic machines	0	0	4	4	4
Increment in output	106,600	-88,400	538,200	899,600	865,800

Figure 9 - Classifications of the scenarios for the automotive manufacturing cell

module, there would be a strong depletion in the monthly output. However, this scenario is economically feasible because it would result in a reduction of one operator. The other scenarios can be analyzed similarly.

Still analyzing Figure 9, it can be observed that four scenarios are economically attractive since the NPV is higher than zero. From the economic view point, the best scenario is C (purchase of four automatic machines), because the NPV is the highest. However, the company might not have the demand to support this scenario production.

In the same way as in the automotive manufacturing cell, the transponder *B* cell can be analyzed. Figure 10 shows a graph that classifies the eleven scenarios in order of increasing NPV and also shows the increment in the monthly output that each scenario generates.

By looking at the graphic above, scenario B does not consider any new investment, but it considers two more operators per work shift. The addition of two more operators generates an increment of thirty nine transponders *B* monthly and it results in an NPV in the order of four million Reais (approximately US$ 2,127,660). The other scenarios can be analyzed in the same way.

Still analyzing Figure 10, it can be observed that ten out of the eleven scenarios are economically attractive since the NPV is higher than zero. Only scenario ABDE is not economically feasible.

From the economic view point, the best scenario is BCE, because the NPV is the highest. However, the company might not have the demand to support this

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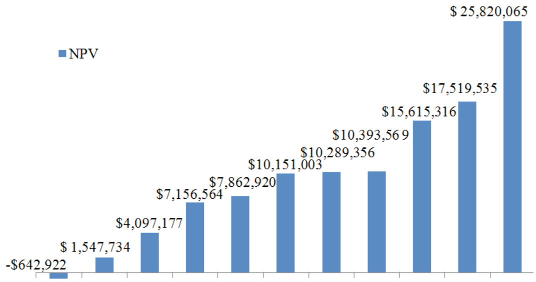

	ABDE	C	B	ACDE	E	CE	BC	ADE	BE	AD	BCE
Workbench without equipment	1	0	0	1	0	0	0	1	0	1	0
Quantity of work shift	1	0	0	1	1	1	0	1	1	0	1
Operators for work shift	1	0	2	0	0	0	2	0	2	0	2
Workbench with equipment	0	1	0	1	0	1	1	0	0	0	1
Increment in output	1	16	39	79	81	104	99	105	155	166	253

Figure 10 - Classifications of the scenarios to the transponder B cell

scenario production. So, the decision makers can know the NPV of a scenario that attends a forecasted demand for transponders *B*.

Another analysis that can also be done is the comparison among scenarios. For example, if the company wants to increase the monthly output, but it does not want to have a new shift, the best scenario is BC. This one is economically better than many scenarios that have a new work shift (E and CE). By looking at the graph, it is more economically feasible to hire two more operators (scenario B) than only buying new pieces of equipment (scenario C).

When dealing with an industrial investment there are variability and uncertain data associated. With this in mind, the contribution margin can vary according to the client. The total produced in a month and the cost associated with that can also change over 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, it is important information to know the probability of an investment being unfeasible before performing any industrial investment, in other words, by knowing that the probability of the NPV of each scenario being less than zero. As referred to in Van Groenendaal and Kleijnen (1997), the probability of the NPV of a scenario being less than zero is calculated in the estimated probability distribution to the NPV of this scenario.

All things being considered, a Monte Carlo simulation was performed, via Excel® and Crystal Ball®. Three input variables were considered with their respective

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probability distributions: contribution margin, costs and total produced monthly. The output variable is the NPV, that is, the desirable probability distribution.

Figure 11 shows the probability of the NPV for scenario C (buying one more workbench with pieces of equipment) being less than zero. This probability is 6.3%. This means that there is 6.3% chance that the NPV is less than zero. The other scenarios can be analyzed in the same way.

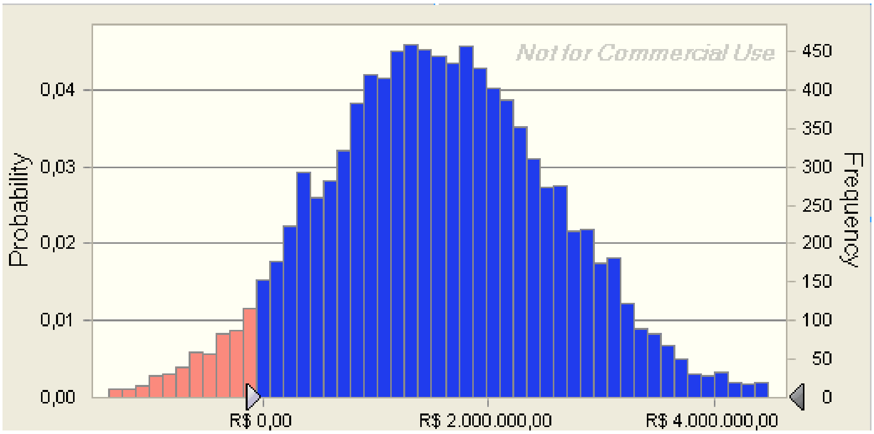
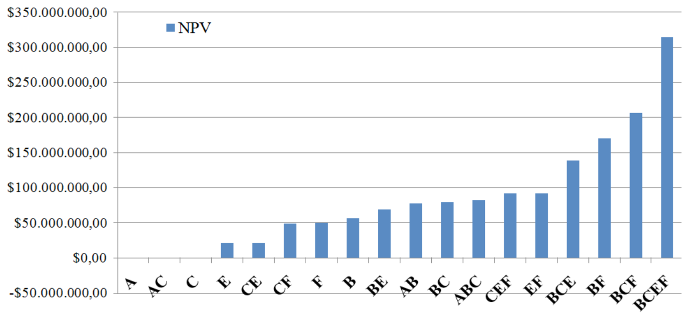


Figure 11 - Probability associated with the scenario C to the transponder B cell

Finally, for the transponder *A* cell, Figure 12 shows a graph that classifies the eighteen scenarios according to the respective NPV´s in increasing order and also shows the increment in the monthly output that each scenario generates.



Workbench without equipment	0	2	2	0	2	2	0	0	0	0	2	2	2	0	2	0	2	2
Oprerators for work shift	0	0	0	0	0	0	0	3	3	3	3	3	0	0	3	3	3	3
Workbench with equipment	2	2	0	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0
Quantity of shift	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 12 - Classifications of the scenarios to the transponder A cell

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For this application, scenario E does not consider any new investment, since it considers an improvement in the production process flow, by eliminating the project update activity. This improvement generates an increment of eighty transponders monthly (35% of increase in the current monthly output) and it results in an NPV in the order of twenty million Reais (approximately US$ 10,638,298). The other scenarios can be analyzed in the same way.

When the simulation team presented this result to Padtec's decision makers, they made sure that scenario E was applied in the transponder *A* production cell. Their intention was to verify if the forecasted results by the simulation model (scenario E) would be confirmed in the real world. It is known in the simulation literature 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).

This procedure occurred as follows: a PCBs batch was updated by the supplier and the production cell received the PCBs ready for the components assembly. This real test showed a monthly production of transponders *A* just 6% smaller than the simulation model prediction (scenario E).

Therefore, the simulation model presented in this paper received credibility by the decision makers. The results reached in practice were favorable and were close to the results forecasted by the simulation model. This scenario E was successfully implemented in Padtec's transponder *A* production cell.

Still analyzing Figure 12, it can be perceived that fifteen scenarios are economically attractive since the 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 BCEF, because the NPV is the highest. However, the company might not have the demand to support this scenario production. So, it is possible for the decision makers to know the NPV of a scenario that attends a forecasted demand for transponder *A*.

Another analysis that can also be made is the comparison among scenarios. For example, if the company wants to increase the monthly output, but it does not want to have a new shift, the best scenario is BCE. This one is economically better than many scenarios that have shift (F, CF, CEF and EF).

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

In order to know the probability of the NPV of each scenario being less

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than zero a Monte Carlo simulation was performed, 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 13 shows the probability of the NPV for scenario A (buying one more workbench with pieces of equipment) to be less than zero. This probability is 56%. It means that, there is a 56% chance of the NPV being less than zero. The other scenarios can be analyzed in the same way.

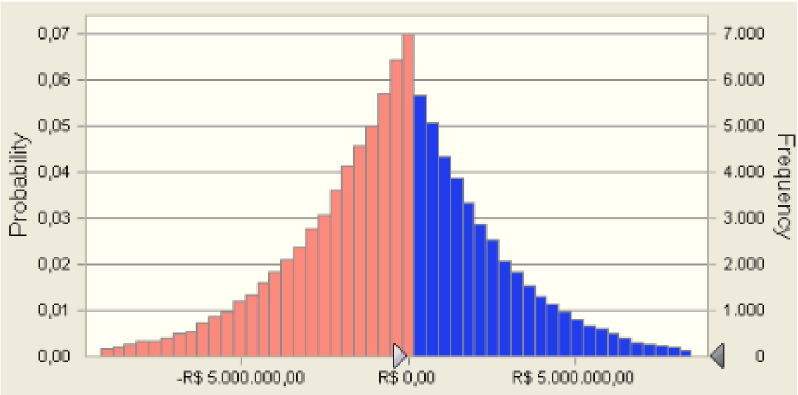

Figure 13 - Probability associated with scenario A for the transponder A cell

Conclusions

Definitely, discrete event simulation models, design of experiments and economic analysis can be combined to aid the decision making process in the manufacturing systems evaluation.

We demonstrate the use of a sequence of steps to perform an economic evaluation of scenarios for manufacturing systems through discrete event simulation based experiments in three examples from two companies.

The three examples presented show how the net present value analysis can be developed in manufacturing systems through verified and validated models, full factorial designs and economic analysis. This way the simulation model is able to generate output to enter in the cash flow with more accuracy in comparison to data based only the experience of a process specialist or arbitrary data.

Without the flexibility of a computational simulation model, performing all these experiments would be very expensive or even impracticable in practice.

Additionally, the simulation conceptual models allowed the process specialists to document and gain more knowledge under the production process. In the case of the transponder *A* cell this conceptual model allowed the identification of an

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activity that should not exist inside the production process (project updating). Padtec applied a scenario that eliminates this activity and the results from the real system were increase close to the results pointed by simulation (35% of increase in the current monthly output). The simulation model gained credibility among the decision makers.

Another possibility that can be observed is to perform a Monte Carlo simulation to know the probability of the NPV associated with each scenario being less than zero, since the economic variables can change over the time.

This work is concluded by highlighting the design of experiments role to select the most relevant scenarios to be economic analyzed, when there are a lot of scenarios. As we demonstrated through the three objects of study, as the number of factors grows the utility of design of experiments to select the relevant scenarios before the economic analysis increases. This fact is observed because of the advantage of saving time in the construction of the cash flow only for the significant scenarios instead of building a cash flow for all possible scenarios (eight, thirty two, sixty four, etc.)

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