APPLICATION OF FACTORIAL DESIGNS FOR REDUCING FACTORS IN OPTIMIZATION VIA DISCRETE-EVENT SIMULATION

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ABSTRACT

Optimization via simulation came true; most discrete-event simulation packages have some kind of optimization routines but the optimum search can become very time-consuming as the factor number increases. This paper objectives show how Factorial Designs help the optimization via simulation to reach the optimum solution by reducing number of factors. A comparative study between an optimization without planning and an optimization planned based on Factorial Designs is carried out. Results are presented where the reduction of the number of runs needed to find the optimum is showed. This work concludes with brief considerations on the Factorial Designs and optimization via simulation integration.

1 INTRODUCTION

The manufacturing system simulation modeling is dated back to at least the early 1960´s (Law and Mccomas 1998) and became one of the most popular and powerful tools employed to analyze complex manufacturing systems (O'Kane 2000; Banks 2005). According to O'Kane (2000), one way to forecast the behavior of these systems is using discrete-event simulation which consists in modeling a system where changes occur at discrete-time intervals. It is appropriated for manufacturing systems as their behavior changes in such way.

Some manufacturing issues addressed by simulation include specifying the need and quantity of equipment and personnel, performance evaluation, and evaluation of operational procedures (Law and Mccomas 1998). The simulation's objectives are classified as performance analysis, capacity/constraint analysis, configuration comparison, optimization, sensitivity analysis and visualization (Harrell et al. 2000).

The optimization via simulation deserves a special attention. Harrell (2000) define optimization as the process of trying different combinations of values for the variables that can be controlled in order to seek the combination of values that provides the most desirable output from the simulation model. However, as the number of variables increases, the optimization phase becomes more time-consuming. So, planning the variables which will compound the search space is the best choice to be performed before the optimization. To plan the optimization, experiments could be done using factorial designs, for example.

In this paper, a comparative study between an optimization without planning and an optimization planned through Factorial Designs carried out. The objective of this work is to show how Factorial Designs can help the simulation optimization to reach the "best" solution.

To accomplish this objective, a manufacturing cell is modeled and experimental research is done. This methodology is appropriated because of the facility to establish cause and effect relationship (Bryman 1989).

The remainder of this article is organized as follows: Section 2 introduces discrete-event simulation and presents some considerations on performing a simulation. Section 3 introduces optimization via simulation and gives a very brief Genetic Algorithm (GA) description. The considerations on the construction of cell's simulation model are presented at section 4. The experiments and results analysis are at section 5. The article concludes with some considerations on the integration between Factorial Designs and optimization.

2 DISCRETE-EVENT SIMULATION

Simulation is the process of designing a model of a real system and conducting experiments with such a model. This is done with the purpose of understanding the behavior of the system and/or evaluating various strategies for

the operation of the system (Shannon 1998). Some simulation advantages are:

- One can simulate systems that already exist as well as those that are capable of being brought into existence.
- Simulation allows one to identify bottlenecks in information, material and product flows and to test options for increasing flow rates.
- It allows one to gain insights into how a modeled system actually works and to understand which variables are most important to performance.
- A significant advantage of simulation is its ability to let one experiment with new and unfamiliar situations and to answer "what if" questions.

Some simulation disadvantages are model building requires special training, simulation results can be difficult to interpret, simulation modeling and analysis can be time consuming and expensive, and the misuse of simulation to solve problems when analytical solution is possible or even preferable, and each run of a stochastic simulation model produces only estimates of model's true characteristics for a particular set of input parameters (Law and Kelton 2000, Banks et al. 2005).

In this study, a discrete-event simulation is used which concerns the modeling of a system as it evolves over time by a representation in which the state variables change instantaneously at separate points in time (Law and Kelton 2000). This methodology is ideal to be applied to manufacturing systems because they exhibit discrete production changes (O'Kane et al. 2000).

Some characteristics founded on problems to be analyzed that justified the use of simulation are (Strack 1984, Law and Kelton 2000, O'Kane et al. 2000):

- real-word systems with stochastic elements cannot be accurately described by a mathematical model that can be evaluated analytically;
- it is easier to obtain results from a simulation model than using an analytical method;
- experimentation is impossible or very difficult in a real world system;
- the need of long-period time studies or alternatives that physical models do not provide.

O'Kane et al. (2000) advise following a structured approach when using simulation in manufacturing system studies so that designers can identify within the model, elements of the design which are critical to success. According to these authors, before one begins to apply simulation techniques to manufacturing systems, it is important to be aware of the problems that have to be overcome when attempting to provide solutions to real world situations. These problems comprise tasks as problem and objective definitions through model building, validation and data analysis.

3 OPTIMIZATION VIA SIMULATION

Optimization via simulation is the process of trying different combinations of values for variables that can be controlled in order to seek the combination of values that provides the most desirable output from the simulation model (Harrell et al. 2000). According to Fu (2002), the integration between optimization and simulation is recent and has been occurring since the end of the last millennium and the relationship commonly encountered in commercial software is a subservient one where the optimization routine is an add-on to the simulation engine. This optimization routine needs the simulation engine outputs to find the parameter set which leads to the best solution.

There are several techniques for optimization. Some are based on heuristics. According to Silva and Montevechi (2004), the heuristic techniques accomplish good solutions and even finding the optimum solution. However, it is not possible to state that the solutions found by these techniques are the best ones.

3.1 Genetic Algorithms

One of the heuristic techniques used in optimization software is the Genetic Algorithms (GA), proposed initially by John Holland in 1975 (Goldberg 1989). The Genetic Algorithms are part of a bigger set called Evolutionary Algorithms (EA). The GA's are very attractive to simulation model optimization because they need neither a formal objective function nor mathematically expressed constrains, but the function result only (Silva and Montevechi 2004).

The main idea behind the GA is the smart exploration of a response surface, where simultaneous searches are performed through specific points from this surface. In a similar way to the Theory of Evolution proposed by Darwin (1936), the GA's manipulate a population of points on the response surface or possible solutions from a proposed problem. This is done in such a way that worse solutions fade away, while the better ones continually evolve in their search for the optimum by exploiting diverse areas simultaneously from the response surface (Tanomaru 1995).

In GA's, each individual or possible solution is defined by a chromosome which is also represented by a codification, usually a binary codification. The number of genes of this chromosome is equal to the number of variables of the proposed problem and the number of bits for each gene is defined according to the precision required. Figure 1 shows a representation of a possible solution (chromosome) for maximization problem of a function f(x,y,z,w) with four decision variables and six-bit precision, with f: $\Re n \to \Re$ and search space $S \subseteq \Re n$.
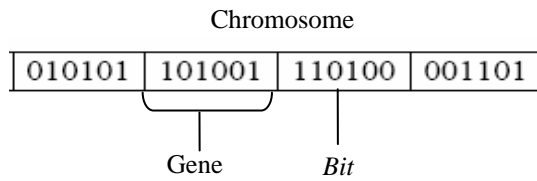
Chromosome

Figure 1: Possible Solution Representation with Four Genes and Six Bits Each. (Source: Silva and Montevechi 2004)

The fitness function defines the fitness or survival chance of each individual in a given population. This function sometimes is the function f(x,y,z,w) itself. However, there are situations where this function needs to be transformed to better represent the fitness of an individual in the population. Hence, a fitness function for f(x,y,z,w) could be represented as G[f(x,y,z,w)]. To evolve the population, the GA's apply genetic operators: selection, cross-over and mutation that have as objective to create new individuals.

The Selection operator offers to the best individuals from population preference to reproduction process, allowing these individuals to pass their characteristics to the next generations. The roulette method is the most utilized method for selection. In this method, *n* individuals are randomly selected with replacement from a population with *n* individuals. Then, their fitness values define the probability of them being chosen, as showed by Equation (1).

$$p(c_i) = \frac{\alpha(c_i)}{\sum_{i=1}^{n} \alpha(c_i)} \qquad (1)$$

where $p(c_i)$ is the probability of the *ith* individual to be chosen, $\alpha(c_i)$ is the fitness value of the *ith* individual and *n* is the number of individuals. At the end, the resultant population has great chance of owning better individuals.

The Cross-over operator creates new individuals combining two or more individuals. The intuitive idea behind this operator is the change of information among different candidate solutions.

The Mutation operator changes randomly an individual characteristic altering a bit value. Hence, the descendant characteristics are limited to ascendant constitution; mutation allows new individuals with characteristics not yet identified to come out (Cunha and Pinto 2001). This change not only assures that the probability of reaching any response surface point is never zero, but it also avoids local optimum.

Cross-over and mutation operators must not be applied to all individuals (Silva and Montevechi 2004). Hence, it is necessary to define the cross-over and mutation rates as well as the size of the population. But, there are not optimum parameters since they are specific for each problem and each codification schema. In addition, they can not be

adopted in a generic way as they compromise the global performance of the algorithm (Cunha and Pinto 2001). Other important parameter to be considered is the stop criteria which depends on the problem and the computational effort required and one can adopt the maximum number of generations, the total duration or a minimum value of standard deviation of individual fitness values (Silva and Montevechi 2004).

4 SYSTEM MODELING

To accomplish the paper's objective, a manufacturing cell is modeled and it is intended to increase the throughput by adding new equipments. This model is deterministic. It means that no source of randomness is modeled and all input data are constant (Law and Kelton 2000, Banks et al. 2005). The project scope is a manufacturing cell called Group #1 from pistol slide shop of a defense material supplier.

In order to accomplish a comparison study, it is created an investment scenario, that is, a loan is done to buy new equipments. The loan payment frequency is monthly and this payment is subtracted from monthly profit which is determined by the monthly production multiplied by unitary profit. The problem is to select the optimum set of equipments which profit's increase compensates the additional equipment's purchase cost giving the best return. There are nine simulation model parameters which can be changed. They represent the quantity of equipments that is available to perform a specific task or operation. They assume two values: 1 or 2. Table 1 presents these parameters.

Table 1: Description of Simulation Model Parameters

	Parameter	Description
1	Neq_Op050	Quantity of equipment available to perform operation 50
2	Neq_Op052	Quantity of equipment available to perform operation 52
3	Neq_Op070	Quantity of equipment available to perform operation 70
4	Neq_Op080	Quantity of equipment available to perform operation 80
5	Neq_Op082	Quantity of equipment available to perform operation 82
6	Neq_Op100	Quantity of equipment available to perform operation 100
7	Neq_Op110	Quantity of equipment available to perform operation 110
8	Neq_Op120	Quantity of equipment available to perform operation 120
9	Neq_Op170	Quantity of equipment available to perform operation 170

The optimum set of equipments is determined by two forms. The first form is performing some experiments to

identify the principal factors and using them as input for the optimization phase. The second one is an optimization using all nine factors.

The following information was obtained on Group #1: composition (the entities), the amount of workers available (the resources), the activities and their durations, shifts and part routes. Table 2 summarizes this information and Table 3 summarizes the activities of the process..

Table 2: System Element Summary

Locations	9 machines
Resources	14 workers distributed at two shifts
Processes	37 activities
Controls	Shifts
	Part routes

Table 3: Process Summary

Quantity of operations	9
Quantity of transportations	19
Quantity of queues	9
Total	**37**

The Promodel 6.0 simulator was used to build the models. Promodel is a discrete-event simulator for manufacturing and material handle systems.

Model verification and validation were performed by two ways. Initially, a plant expert analyzed whether the behavior of the model would appear reasonable. Then, real historical data was compared with simulated results.

5 EXPERIMENTATION

Initially, the experiments are planned to identify the most important factors of the model. Then, these factors are used as input data for optimization software. Also, this model is optimized using all factors as input data in order to compare the results. The optimization software is Simrunner 3.0 which uses Genetic Algorithms and is packaged along with Promodel 6.0.

5.1 Identifying Important Factors

According to Law and Kelton (2000), i*n simulation, experimental designs provides a way to deciding which particular configurations to simulate before the runs are made so the desired information can be obtained with the least amount of simulating*. Considering that there are 9 factors, if it were done a full factorial experiment, it would be necessary 2^9=512 runs. Therefore, a screening experiment must be done.

Screening or characterization experiments are experiments *in which many factors are considered and the objective is to identify those factors (if any) that have large effects* (Montgomery 2001). Typically, screening experiment

involves using fractional factorial designs and it is performed in the early stages of the project *when many factors are likely considered to have little or no effect on the response* (Montgomery 2001). Montgomery (2001) states *in this situation it is usually best to keep the number of factors levels low*, According to this author, two levels work well. So, the experimental design adopted was a two-level nine-factor fractional factorial with resolution IV. Resolution IV means *no main effect is aliased with any others main effect or with any two-factor interaction, but two-factor interactions are aliased with each other* (Montgomery 2001). The resolution IV designs available are 2_{IV}^{9-3}=64 runs and 2_{IV}^{9-4}=32 runs.

The 2_{IV}^{9-4} design was chosen because it has fewer runs than 2_{IV}^{9-3} design. If necessary the former design collapses into a five- or less- factor full factorial since preliminary studies have shown that five factors (Op070, Op080, Op082, Op110 and Op120) are critical to cell performance this design works well. The generators for this design are F=±BCDE, G=±ACDE, H=±ABDE and J=±ABCE and the defining relations are I = BCDEF = ACDEG = ABDEH = ABCEJ = ABFG = ACFH = ADFJ = BCGH = BDGJ = CDHJ = DEFGH = CEFGJ = BEFHJ = AEGHJ = ABCDFGHJ. Table 4 shows the factor assignment to the variables of the design.

Table 4: Variable-Factor Association

Variable	Factor	Low Level (-)	High Level (+)
A	Neq_Op070	1	2
B	Neq_Op080	1	2
C	Neq_Op082	1	2
D	Neq_Op110	1	2
E	Neq_Op120	1	2
F	Neq_Op050	1	2
G	Neq_Op052	1	2
H	Neq_Op100	1	2
J	Neq_Op170	1	2

Table 5 shows the design matrix for principal fraction with the results obtained for each run. The main factor effects are shown in Figure 2. It is noticed that factors B=Neq_Op080, C=Neq_Op082, E=Neq_Op120 have positive effect. These factors increase the profit when they are increased (high level). The other factors have negative effect that decrease the profit when they are increased (high level). This figure gives a good indication that only three factors must be changed, the other factors must not be changed. However, to have conclusive results, it is necessary to verify the interactions among factors.

Table 5: The 2_{IV}^{9-4} Design Matrix Principal Fraction and Results

Run	A	B	C	D	E	F=BCDE	G=ACDE	H=ABDE	J=ABCE	Profit
1	-	-	-	-	-	+	+	+	+	280036
2	+	-	-	-	-	+	-	-	-	299418
3	-	+	-	-	-	-	+	-	-	299518
4	+	+	-	-	-	-	-	+	+	280236
5	-	-	+	-	-	-	-	+	-	314818
6	+	-	+	-	-	-	+	-	+	295436
7	-	+	+	-	-	+	-	-	+	315036
8	+	+	+	-	-	+	+	+	-	295654
9	-	-	-	+	-	-	-	-	+	299418
10	+	-	-	+	-	-	+	+	-	280036
11	-	+	-	+	-	+	-	+	-	280136
12	+	+	-	+	-	+	+	-	+	260854
13	-	-	+	+	-	+	+	-	-	295436
14	+	-	+	+	-	+	-	+	+	276054
15	-	+	+	+	-	-	+	+	+	295654
16	+	+	+	+	-	-	-	-	-	315036
17	-	-	-	-	+	-	-	-	-	309109
18	+	-	-	-	+	-	+	+	+	270345
19	-	+	-	-	+	+	-	+	+	270545
20	+	+	-	-	+	+	+	-	-	270445
21	-	-	+	-	+	+	+	-	+	285845
22	+	-	+	-	+	+	-	+	-	285745
23	-	+	+	-	+	-	+	+	-	391945
24	+	+	+	-	+	-	-	-	+	391945
25	-	-	-	+	+	+	+	+	-	270345
26	+	-	-	+	+	+	-	-	+	270345
27	-	+	-	+	+	-	+	-	+	270545
28	+	+	-	+	+	-	-	+	-	270445
29	-	-	+	+	+	-	-	+	+	285945
30	+	-	+	+	+	-	+	-	-	285845
31	-	+	+	+	+	+	-	-	-	398545
32	+	+	+	+	+	+	+	+	+	359781

The two-factor interactions are shown in Figure 3. It is noticed that the interactions between BC=Neq_Op080 and Neq_Op082, BE=Neq_Op080 and Neq_Op120, CE=Neq_Op082 and Neq_Op120 lead to better results, whereas the interactions between DF=Neq_Op110 and Neq_Op050, GH=Neq_Op052 and Neq_Op100, AJ=Neq_Op070 and Neq_Op170 lead to poor results.

Taking into consideration interactions DF, GH and AJ, it is clear that factors A, D, F, G, H and J must be kept at low level (1) and factors B, C and E must be changed to the high level (2). However, in order to check if it is the best solution, an optimization using these three factors is performed. Following, an optimization using all nine factors is performed to compare their performance.

5.2 Optimization Using Three Factors

In this optimization phase, the three factors B, C and E are selected as inputs. The values these parameters can assume are 1 or 2. The other factors are kept at their original values. The objective function is to maximize the profit as presented earlier in section 4. After 8 runs, the Simrunner stops the search. The best result found is 411.327 which corresponds to experiment #6, as presented in Figure 4. The parameter values are presented in Table 6.
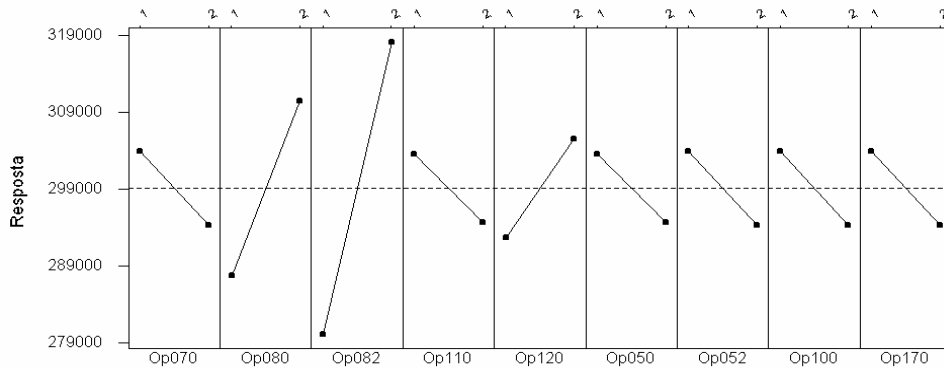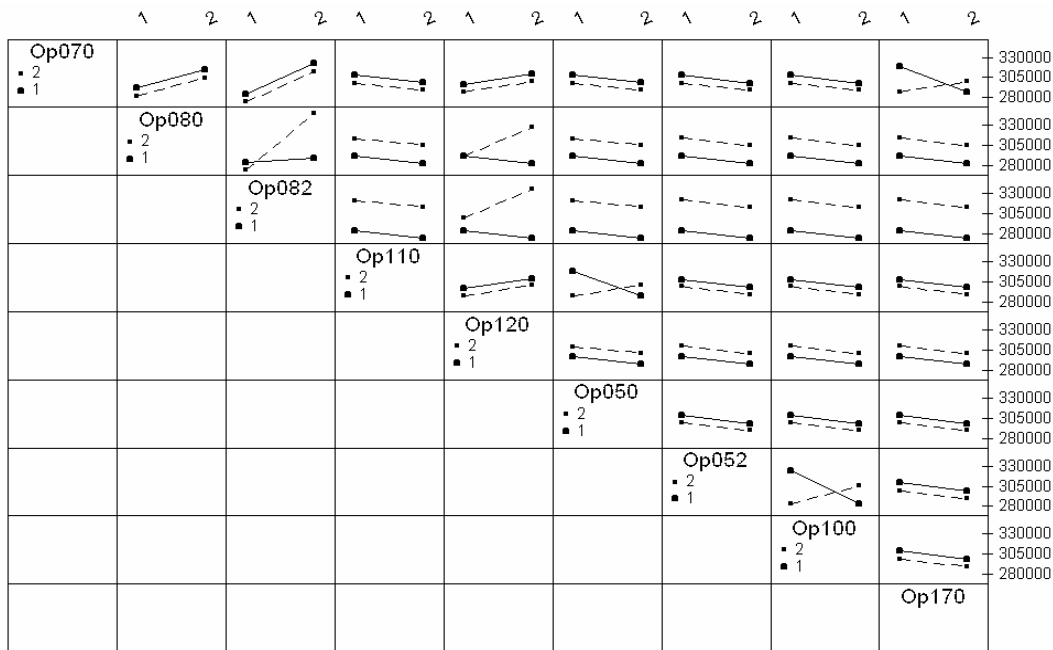
Figure 2: Main Effects Plot for Profit

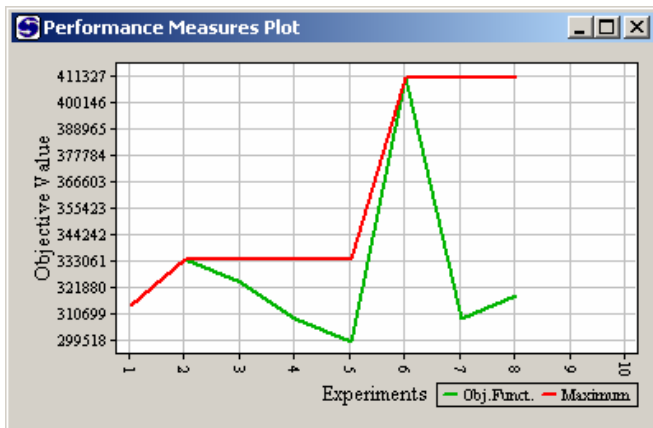Figure 3: Two-Factor Interaction Plot for Profit

Figure 4: Simrunner's Performance Measures Plot for Optimization Using Three Factors

Table 6: Best Solution for Optimization Using Three Factors

Parameter	Value
Neq_Op080	2
Neq_Op082	2
Neq_Op120	2

5.3 Optimization Using All Factors

In this optimization phase, the nine parameters presented in Table 1 are selected as inputs. The values these parameters can assume are 1 or 2. The objective function is to maximize the profit, as presented earlier in section 4.

After 98 runs, the Simrunner stops the search. The best result found is 411.327 which corresponds to experiment

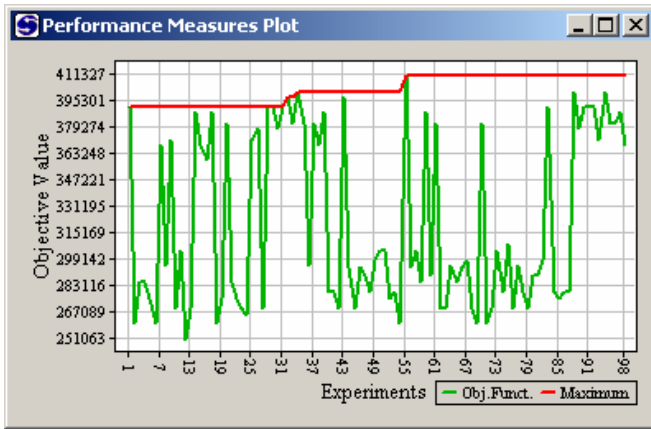#55 as presented at Figure 5. The parameter values are presented in Table 7.

Figure 5: Simrunner's Performance Measures Plot for Optimization Using All Factors

Table 7: Best Solution for Optimization Using All Factors

Parameter	Value
Neq_Op050	1
Neq_Op052	1
Neq_Op070	1
Neq_Op080	2
Neq_Op082	2
Neq_Op100	1
Neq_Op110	1
Neq_Op120	2
Neq_Op170	1

5.4 Result analysis

Table 8 shows the results obtained by the three procedures. The three procedures lead to the same results indicating that there is coherency among them. Taking into consideration the number of runs necessary to optimize the model, it is clear the advantage of determining previously the main parameters and then proceeding the optimization using them versus to proceed the optimization using all factors. The former demanded 32+8=40 runs to obtain the best result against the 98 runs from the latter, a reduction of 59% in the number of runs. Considering only the runs used in the Factorial Design, 32 runs versus 98 runs from optimization using all factors, the reduction is about 67%.

For this application, since the optimization factor levels and the Factorial Design levels are equal, the optimization using three factors seems meaningless. However, other applications where the optimization factors could have several levels or even were continuous, the Factorial Designs would only identify the main factors without specifying their optimum values.

Table 8: Results from the Three Procedures

Parameter	Factorial Design	Optimization using 3 factors	Optimization using all factors
Neq_Op050	1	1 (*)	1
Neq_Op052	1	1 (*)	1
Neq_Op070	1	1 (*)	1
Neq_Op080	2	2	2
Neq_Op082	2	2	2
Neq_Op100	1	1 (*)	1
Neq_Op110	1	1 (*)	1
Neq_Op120	2	2	2
Neq_Op170	1	1 (*)	1
Result (profit)	411327	411327	411327
Number of runs	**32**	**8**	**98**

The parameters identified with (*) were not used as input for optimization. They were kept at low level (1).

6   CONCLUSIONS

The objective of this work was to show how the Factorial Designs can help the simulation optimization to reach the "best" solution. First, the more relevant model's factors were identified using Factorial Designs. Afterwards, two optimization were carried out: one using the factors previously identified, and the other using all model's factors.

For this application, the solutions obtained from optimization were the same but the numbers of runs were significantly different. The Factorial Designs reduced up to 59% of the numbers of runs needed to find the optimum solution. As the optimization factor levels and the Factorial Design levels were equal, the optimization phase was unnecessary and the runs reduction went up to 67%.

For complex system simulation, where the simulation itself is very time-consuming, the Factorial Designs make possible some special approaches as regression metamodels and response surface methodology (Kleijnen 1998) which are recommendations for future works.

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