Process and Product Optimization Using Game Theory

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ABSTRACT

Game Theory has not been explored so far in multi-objective optimization problems developed in the Response Surface Methodology framework, though optimization of multiple characteristics of process and product is a usual problem faced by practitioners in (non)manufacturing environments. In this paper the Stackelberg's technique complemented with a Factors Scaling tool is proposed for finding equilibrium solutions to this type of problem. No subjective information (shape factors, weights and/or other preference information) is required from the practitioners to use this approach, and basic computational background is enough for implementing it. Two case studies provide evidence of the proposed approach ability to achieve nondominated solutions, which validates its usefulness for practitioners who are involved in the multi-response optimization of process and product.

CCS CONCEPTS

• **Applied computing**; • **Operations research**; • **Decision analysis**; • **Multi-criterion optimization and decision-making**;

KEYWORDS

Bi-objective, Stackelberg, Factors Scaling, Multi-response, Pareto, Optimal, Robust, RSM

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1 INTRODUCTION

To identify the input variables settings that yield an optimal solution for multiple objectives (quality characteristics or responses) that are, in general, in conflict, it is the desired result for multi-objective optimization problems. Desirability function-based and loss function-based optimization functions are the most popular optimization functions for multi-objective optimization among researchers and practitioners who use the Response Surface Methodology (RSM) to generate data and fit regression models to objective functions (responses). For an extensive review on these optimization functions the reader is referred to [1-4]. The applicability and computational aspects of various optimization functions in different decision-making contexts were discussed in [5], where the foremost approaches are categorized and integrated as well.

Bi-objective optimization (BOO) is a particular case of multi-objective optimization that is often employed in practice and has been investigated by academics [6-7]. Its aim is to optimize two responses, two mean responses or the mean and standard deviation of a process's or a product's quality characteristic. Various methods have been put forward in the literature for this purpose in the RSM framework, including priority-based, mean squared-based, desirability-based, goal programming-based, and global criterion-based methods. A review on these methods is available in [5, 8-9].

Game Theory usefulness in BOO has not been explored so far, though it has been often used in various social science domains like political science, psychology, economics, sociology, and successfully extended to many other knowledge domains, including finance, accounting, and marketing domains [10-13]. Thus, the objective of this paper is to employ Game Theory in industrial (engineering) problems, namely the Stackelberg's technique complemented with an easy-to-use tool to improve its efficiency, for evaluating its usefulness for solving BOO problems.

The remaining of this article is structured as follows: next section includes an overview on Game Theory and Stackelberg technique. Section 3 presents the results from two case studies. Results discussion is presented in Section 4 and the Conclusions in Section 5.

2 GAME THEORY – AN OVERVIEW

Game Theory is an open research field and has been employed in real-life problems as diverse as arms control policies, dating and marriage, college selection, human organ transplant, environmental cooperation, asset pricing, security at infrastructures (airports, wireless networks, ...), and supply chains design. As a study of strategic interactions in a decision-making process, Game Theory is a mathematical tool that provides a common language to formulate, structure, analyse, and understand the interaction among rational agents (players) and their strategies or decisions/actions. Its impact

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on society has been recognized by the Royal Swedish Academy of Sciences by awarding several game theorists with the Nobel Prize in economics [14].

2.1 Equilibrium Concepts

It is widely accepted that the most favourable solutions for multi-response optimization problems are the called nondominated solutions, or by other words, solutions that belong to the called nondominated solutions set or Pareto front [15]. Notice that a solution is nondominated if the outcome of any objective or payoff function cannot be improved without degrading the outcome of any other objective or payoff function.

In practice, dominated solutions can be also achieved by using the Game Theory, namely the Stackelberg technique, or any other optimization method or technique for solving BOO problems in addition to solutions that are near the Pareto font. However, the later ones must not be ignored because all generated solutions have variability associated and when implemented in practice can yield results similar to those of nondominated solutions. As it is pointed out in [16], equilibrium solutions are expected outcomes for multi-response optimization problems with multiple decision-makers whose objectives are in conflict. Nevertheless, they argued that practitioners should always look for Pareto-Optimal-Equilibrium (POE) solutions.

2.2 Stackelberg Games and BOO

In a Stackelberg (leader-follower) game a hierarchy among the players always exist. In a game with two players, that one who holds the dominant position is called the leader and plays first than the other player, the follower, who reacts (rationally) to the leader decision. Examples of the growing interest and relevance of leader-follower games are reported in [17-20]. However, the Stackelberg technique, has not been tested in BOO developed in the RSM framework, where the simultaneous optimization of the models fitted to two responses (two means or a mean and a standard deviation), either converting or not converting those models into a composite function, is a current practice in industry and an active research field [6-7]. Thus, it is pertinent to state if Stackelberg technique can yield POE solutions for (games) BOO problems developed in the RSM framework.

In a hierarchical (leader-follower or Stackelberg) game, assuming that $f_1(X)$ and $f_2(X)$ represent the polynomial (second order) models fitted to responses, as example, the estimated mean ($\hat{\mu}$) and estimated standard deviation ($\hat{\sigma}$) responses, two types of games can be formulated: 1- Leader optimises the estimated mean response and the follower optimizes the estimated standard deviation response; 2- Leader optimizes the estimated standard deviation response and the follower optimizes the estimated mean response. In each type of game there are three possible scenarios, as shown in Table 1 and Table 2.

Leader-Mean type games consist of optimizing $\{f_1(X),\ f_2(X)\} = \{\hat{\mu}(X),\ \hat{\sigma}(X)\}$ while the Leader-Standard Deviation type games consist of optimizing $\{f_1(X),\ f_2(X)\} = \{\hat{\sigma}(X), \hat{\mu}(X)\}$. Nevertheless, notice that, in a Leader-Mean type game, when the objective is to set the estimated mean response on target minimizing the estimated standard deviation, the leader optimizes $f_1(X) = (\hat{\mu}(X) - \tau)^2$ or

Table 1: Leader-Mean Games

Leader	Follower
Minimize the estimated mean Set the estimated mean on target Maximize the estimated mean	Minimize the estimated standard deviation

Table 2: Leader-Standard Deviation Games

Leader	Follower
Minimize the estimated standard deviation	Minimize the estimated mean Set the estimated mean on target Maximize the estimated mean

$(\hat{\mu}(X) - \tau)$ and the follower optimizes $f_2(X) = \hat{\sigma}(X)$, where τ represents a target value and X represents a vector of input variables. The corresponding inverted game is a Leader-Standard Deviation type game, where the leader optimizes $f_1(X) = \hat{\sigma}(X)$ and the follower optimizes $f_2(X) = (\hat{\mu}(X) - \tau)^2$ or $(\hat{\mu}(X) - \tau)$.

In a Stackelberg game, the leader is the first one to play (maximize, minimize, or set on target its objective function using, as example, the Excel®-Solver tool) by processing one or more input variables (x_l) from X. Then, the follower reacts processing the remaining input variables (x_j) from X, keeping x_l unchanged. This sequential procedure stops when the leader cannot improve his/her payoff or outcome, which means that a Stackelberg equilibrium point is found. This solution is called a Pareto-optimal equilibrium point (a nondominated solution) if an improvement in $f_1(X)$ is achieved without degrading the value of $f_2(X)$.

2.3 Stackelberg Game: Input Variables Selection

To minimize the number of games and to find an equilibrium or nondominated solution, this is, to improve the effectiveness of a Stackelberg game, the Factors Scaling tool was selected and employed here due to its application easiness and efficacy. Factors Scaling enables to combine main effects, quadratic effects, and interactions of a second order model into a meaningful summary that allows the practitioner/data analyst to identify the most influential input variables in each response [21]. The 'relative importance' of the input variables or factors (MPI_{nk}^{std}) can be defined as

$$MPI_{nk}^{std} = MPI_{nk} / \left(max_{n=1,\ldots,N}\, |MPI_{nk}|\right) \quad (1)$$

where MPI_{nk} (2) denotes the maximal absolute change in the k-th response that can be induced by increasing X_n (n = 1, . . ., N) by a value H, for a certain starting value of X_n and some favorable setting of the other factors included in the model fitted to that response [21].

$$|MPI_{nk}| = H\,|\beta_{nk}| + H^2\,|\gamma_{nk}| + (H * H)\,\left[\sum_{m=n+1}^{N} |\delta_{nmk}| + \sum_{m=1}^{n-1} |\delta_{nmk}|\right] \quad (2)$$

where H takes a value equal to one (half-range on range [-1, 1]) or equal to 1.682 (half-range on range [-1.682, 1.682]) depending on the experimental space, β_{nk} represents the regression coefficients of the linear effect of X_n in the model fitted to k-th response, γ_{nk} represents the regression coefficients of the quadratic effect of X_n, and δ_{nmk} represents the regression coefficients of the interaction effect between X_n and X_m (n = 1, . . . , N − 1; m = n + 1, . . ., N) in the model fitted to the k-th response.

3 CASE STUDIES

Two BOO problems were selected from the literature to illustrate and evaluate the Game Theory usefulness in this type of problems. A Leader-Mean and a Leader-Standard deviation approaches (see Tables 1-2) are tested in both case studies to better understand the Stackelberg technique working ability to generate POE solutions and the usefulness of the Factors Scaling tool.

3.1 Case Study 1 - Coating Thickness of Bare Silicon Wafers

Shin and Cho [22] presented a case study whose objective was to optimize the coating thickness of bare silicon wafers, namely the mean response deviation to a target and the standard deviation values. Three key factors affect the process: mould temperature (x_1), injection flow rate (x_2), and cooling rate (x_3). The models fitted to the mean response ($f_1(X)$), whose target value was 71.14, and to the standard deviation ($f_2(X)$), whose value must be as smaller as possible, are as follows (see [22] for details):

$$f_1(X) = \hat{\mu} = 2.21 + 0.59 \; - 0.35 \; - 0.01 \; + 0.28 \\ +1.29 \; + 1.85 \; + 0.18 \; + 3.32 \; + 3.02$$

$$f_2(X) = \hat{\sigma} = 2.55 + 0.38 - 0.43 \; + 0.56 \; + 0.49 \\ +0.61 \; + 0.85 - 0.94 \; + 1.44 - 0.24$$

These two objective functions and the three variables enable to formulate twelve Stackelberg games. Six games where the Leader optimizes $\hat{\mu}$ selecting one or two variables and the follower optimizes $\hat{\sigma}$ using the remaining variable(s), and six games where the Leader optimizes $\hat{\sigma}$ selecting one or two variables and the follower optimizes $\hat{\mu}$ using the remaining variable(s). Examples of these games are shown in Figure 1. In this figure only six solutions are shown because the same solution is achieved by inverting the players hierarchy in a game. As example, $\hat{\mu}(x_2, x_3) - \hat{\sigma}(x_1)$ and $\hat{\sigma}(x_1) - \hat{\mu}(x_2, x_3)$, or $\hat{\mu}(x_1) - \hat{\sigma}(x_2, x_3)$ and $\hat{\sigma}(x_2, x_3) - \hat{\mu}(x_1)$ yield the same solution. Figure 1 also includes the Pareto frontier for this case study considering the responses constrains.

This case study shows that Stackelberg technique can capture the ideal solution for this problem, the one that is represented in Figure 1 by a plus sign. The other solutions, except the one that is represented by the cross, are also balanced solutions so they cannot be discarded as alternatives to the ideal solution (represented by the plus sign), despite the increment in their standard deviation value. Table 3 is an example of the optimization procedure with the Stackelberg technique for the referred game, and one can see that the final solution is achieved after two Leader-Follower cycles. The number of cycles in the other games ranges from 2 to 16 cycles.

Concerning the variables selection, the Factors Scaling tool provide the necessary guidance to achieve the most favourable solutions. In fact, when the leader and the follower play with the variables with the highest influence on their function, x_3 and x_1, respectively (see Table 4), the best possible solution (that represented

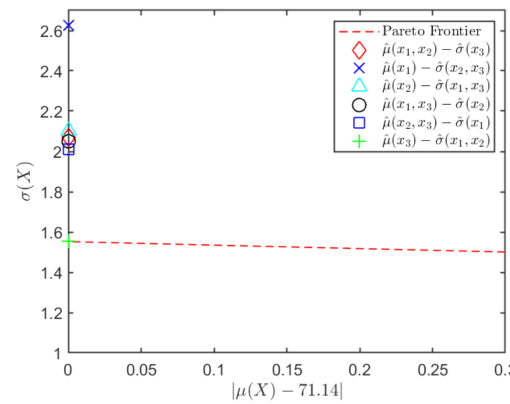

Figure 1: Pareto Frontier and Stackelberg Solutions.

by the plus sign), a POE solution, is achieved. All the other solutions have a slightly high standard deviation value, but their mean value is on target as well. Conversely, when both the leader and the follower play with the less influential variables, a less favourable solution is achieved. As example, the game ($\hat{\mu}(x_1) - \hat{\sigma}(x_2, x_3)$) yields the solution with the highest variability. These results provide strong evidence of Factors Scaling tool usefulness.

3.2 Case Study 2 - Cutting Machine

To optimize the metal removal rate of a metal cutting machine, the effects of speed (x_1), depth (x_2), and feed (x_3) were evaluated from an experimental study [23]. The models fitted to the mean and standard deviation responses, presented below, are obtained from the results of a central composite design with eight factorial points, six axial points, and six centre points replicated three times (see [23] for details). In the optimization procedure it was assumed that the mean response ($\hat{\mu}$) is of the nominal-is-best type, with target equal to 71.14 in the range [69, 83], and the variance ($\hat{\sigma}^2$) is of the smaller-the-better type.

$$f_1(X) \; = \hat{\mu} = 79.8568 + 1.2073 \; - 0.1540 \; + 0.0706 \; - 1.4708 \\ +0.7542 \; + 0.8708 \; - 2.0421 \; - 0.1922 \; - 0.4456$$

$$f_2(X) \; = \hat{\sigma} = 2.8165 + 0.1040 \; + 0.3436 \; - 0.1484 \; + 0.6371 \\ -0.1763 \; + 0.9729 \; - 0.2595 \; - 0.1087 + 0.0203$$

Following the rational of the previous case study, whenever a game and its inverse game (inverted game hierarchy) solutions are equal, only one game and the respective solution symbol is graphically represented. Figure 2 shows the Stackelberg solution for nine games, and the Pareto frontier. This provides evidence that inverting the players hierarchy in a game does not always mean that the same solution will be achieved. Examples of these games are: 1- Leader optimizes $\hat{\mu}(x_1, x_3)$ and the Follower optimizes $\hat{\sigma}^2(x_2)$, whose solution is represented by the cross; 2- Leader optimizes $\hat{\sigma}^2(x_2)$, and the Follower optimizes $\hat{\mu}(x_1, x_3)$, whose solution is represented by the left-pointing triangle. Tables 5-6 are examples of games development, and one can see that final solutions are achieved only with one Leader-Follower cycle. The number of cycles in the other games ranges from 1, in the games whose solutions

Table 3: Game $|\hat{\mu}(x_3) - 71.14| - \hat{\sigma}(x_1, x_2)$

Iteration	Output improvement	Variables			Leader-Mean	Follower-Mean
		x_1	x_2	x_3	$\|\hat{\mu}(x_3) - 71.14\|$	$\hat{\sigma}(x_1, x_2)$
Start		1.000	1.000	-1.000	1.420	1.750
Leader	Yes	1.000	1.000	-0.583	0.000	1.923
Follower	Yes	1.682	1.682	-0.583	0.846	1.705
Leader	Yes	1.682	1.682	-0.684	0.000	1.552
Follower	No	1.682	1.682	-0.684	0.000	1.552

Table 4: Input Variables Influence on Responses

$f_1(X) = \hat{\mu}$			
	x_1	x_2	x_3
$\|MPI_{n1}^{std}\|$	0.5040	0.5732	1.000
$f_2(X) = \hat{\sigma}$			
	x_1	x_2	x_3
$\|MPI_{n2}^{std}\|$	1.000	0.6608	0.9247

are represented by the triangle and the plus sign, to 8 cycles in the game whose solution is represented by the hexagram.

This case study also enables to affirm that Stackelberg technique can capture POE solutions in DRO problems developed under the RSM framework, such as shown in Figure 2. Notice that eight games (those whose solutions are represented by the plus sign, diamond, hexagram, cross and triangle) yield nondominated solutions, six of them have the mean on target, those represented by the plus sign, hexagram, diamond and cross. The solutions represented by the circle and the left-pointing triangle are at a negligible distance from Pareto frontier so they can also be considered as alternatives to POE solutions, in contrast to those solutions represented by the square and the right-pointing triangle, which are dominated solutions.

As in previous case study, Factors Scaling tool usefulness is confirmed; a POE solution is achieved when the leader, and the follower, play with the variables with the highest influence on their functions (see Table 7). Solutions represented by the triangle and the cross are examples of solutions that confirm it. In this case study, even when none of the players use the variable with the highest influence on its function a POE solution was achieved. For example, in the game $\hat{\mu}(x_2, x_3) - \hat{\sigma}^2(x_1)$, where both players play with the variable with the lowest influence on their function, a POE solution was achieved (that represented by the plus signal (+) in Figure 2).

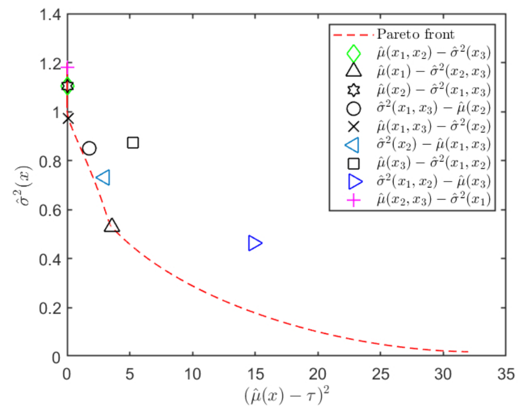

Figure 2: Pareto Frontier and Stackelberg Solutions.

4 RESULTS DISCUSSION

Stackelberg technique presented and illustrated here does neither require any advanced statistical and computational background nor subjective information (weights, shape factors, or other preference information) from the users, who can implement it in an Excel´s spreadsheet. In addition, it can capture POE solutions. These are appealing characteristics which contrast to the overload of preference information required from the decision-makers and the high level of computational, mathematical, and statistical expertise required for using other more popular methods for multi- or bi-objective optimization.

It is known that it may not exist any advantage in using methods mathematically and computationally too sophisticated, because easy-to-implement methods can generate nondominated (optimal) solutions and depict Pareto frontiers similar to those achieved by sophisticated methods [24-25]. This paper confirms it, but there is no guarantee it yields one or more competitive solutions for any case

Table 5: Game $\hat{\mu}(x_1, x_3) - \hat{\sigma}^2(x_2)$

Iteration	Output improvement	Variables			Leader-Mean	Follower
		x_1	x_2	x_3	$(\hat{\mu}(x_1, x_3) - \tau)^2$	$\hat{\sigma}^2(x_2)$
Start		-1.682	0.000	0.000	0.826	0.907
Leader	Yes	-1.682	0.000	0.413	0.114	0.972
Follower	No	-1.682	0.000	0.413	0.114	0.972

Table 6: Game $\hat{\sigma}^2(x_2) - \hat{\mu}(x_1, x_3)$

Iteration	Output improvement	Variables			Leader-Variance	Follower
		x_1	x_2	x_3	$\hat{\sigma}^2(x_2)$	$(\hat{\mu}(x_1, x_3) - \tau)^2$
Start		-1.682	0.000	0.000	0.907	0.826
Leader	Yes	-1.682	0.413	0.000	0.588	3.367
Follower	Yes	-1.682	0.413	0.226	0.732	3.024
Leader	No	-1.682	-0.413	0.226	0.732	3.024

Table 7: Input Variables Influence on Responses

Mean			
	x_1	x_2	x_3
$\lvert MPI_{n1}^{std} \rvert$	1.0000	0.5267	0.4238
Variance			
	x_1	x_2	x_3
$\lvert MPI_{n2}^{std} \rvert$	0.5901	1.0000	0.6541

study. In both case studies presented here, the proposed approach did capture solutions in close agreement with those generated by more sophisticated methods, including POE solutions, which are reached, in general, after a small number of Leader-Follower cycles, though Stackelberg technique is not designed to depict Pareto frontiers. It is also important to point out that to capture a set of solutions evenly distributed along a Pareto frontier, besides an appropriate starting point for input variables, the curvature of objective functions must be manipulated through an exponent [26-29], which is not possible by using the Stackelberg technique. Moreover, to depict a Pareto frontier is not easy for practitioners who don't have advanced computational, mathematical, and statistical expertise and is always a laborious task, which also includes a purge in the generated solutions because all methods generate many dominated solutions among the nondominated ones. In this setting, the presented case studies provide evidence of the Stackelberg technique usefulness, at least as an exploratory tool for bi-objective optimization in the early phases of process and product design and development.

Regarding the selection of input variables, both case studies suggest that Factors Scaling tool can provide helpful guidelines to that purpose. In fact, this tool enables the players know the most influential factors across multiple responses and lead to a better definition of their strategy. In both case studies, nondominated solutions, were achieved when the leader and the follower play with the variables with the highest impact on their optimization functions.

5 CONCLUSIONS

Two case studies from the literature show that Game Theory/Stackelberg technique can be applied in real-life problems developed under the RSM framework. The strengths and weaknesses of Stackelberg technique are exposed and its solutions evaluated in terms of their Pareto-optimality. The Factors Scaling tool integration into the Stackelberg technique is illustrated and results provide evidence of its usefulness.

In both case studies, nondominated solutions were achieved using the proposed easy-to-use approach. Nevertheless, to further evaluate the proposed approach working ability in Bi-objective optimization problems, other case studies must be tested in future work. The uncertainty in the responses model, responses correlation, and the variability in the responses value cannot also be omitted in that work as well.

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