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Sequential experimentation to perform the Analysis of Initial Situation

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Abstract

In this paper, an approach to combine optimization methods and methods from TRIZ will be introduced. The aim is to propose a cross-fertilization of sequential experimentations, an optimized way to build Design of Experiments and to find the best solution for a given problem, and the formulation, and of course resolution, of contradictions. The idea is to search through sequential experimentation if a solution fits all the requirements of a given specs. If it does the problem is considered solved, if not, the problem is considered an inventive one. Then methods of TRIZ can be applied. But the approach proposes an extraction of contradiction out of the sequential experimentation, as these techniques enable to limit the number of elements considered in the problem and to focus only on few but main elements describing the problematic situation. As the focusing on the few but main elements of the problem is one the key objective of ARIZ methodologies, one can consider that sequential experimentation is complementary to TRIZ based methods and that it can provide a good way to make analysis of initial situation.

Keywords: Cross-fertilization, Design of Experiments, Generalized System of Contradictions

1. Introduction

During its evolution, starting from the end of 50's till the end of 80's, if considering "classical TRIZ" as TRIZ developed under the direction of G. Altshuller, some benefits and some limits in the proposed methods can be recognized. First aim of G. Altshuller was to propose a set of tools to help engineers to be more creative, but then he considered that tools were not enough and that methods were necessary. Moreover the recognition of the existence of laws of technical systems evolution reinforces this need of coherent methods to find robust solutions to problems. TRIZ development has lead to the proposal of a set of methods and tools and to a general approach based on 5 steps:

1. The analysis of initial situation, which objective is to elicit the specific conditions under which problem appears, the inherent contradictions and also to choose the root cause of problem, the prior contradiction to be solved.
2. The definition of the problem. The objective of this step is to clarify the limits of the problem, i.e. the borders in which the solution can be found and thus to specify if the problem is a maxi or a mini problem.
3. The definition of the ideal solution aims to separate lower-level solution from higher-level ones by intensifying the constraints for solution concept synthesis.
4. The definition of the physical solution enables to select relevant information for concept solution synthesis, i.e. to identify inventive mechanisms enabling to satisfy the conditions of the ideal solution.
5. The definition of the technical solution reinforces the concept of the physical solution by defining which resources can be used and how these resources are used to fit the physical solution.

The development of ARIZ is based on the objective to propose a methodological and systematic approach to fulfill these 5 steps. But one can notice that the last Altsuller's version of ARIZ only fit the 4 last steps. The analysis of initial situation has not been developed anymore, the last version incorporating it is ARIZ-85A, and is still one key stake in problem solving process. The matter was the recognition that the proposed method for this step was not as developed as the methods inherent to the other steps, thus it was proposed to develop a specific program to tackle this analysis of initial situation.

Sequential experimentation is a well-known sequence of different mathematical tools. The objective of this sequence is to quickly identify the main parameters enabling the satisfaction of the specs and the most appropriate range of values for these parameters. The most common way to search for an optimal is to use:

- at the first the multivariate analysis,
- then apply factorial designs
- and last determine the response optimum with response surface methods.

This approach is very efficient to find a solution if the solution space defined by the initial set of parameters enable to find a solution. It means if a solution can be found by optimization.

When looking for a new solution, one will always begin to search if it is possible to improve existing system by optimizing it. And finally, if it is not, inventive solutions will be searched for. So it seems relevant to try to go towards cross-fertilization between optimization and inventive approaches. In such an approach the analysis of initial situation will then be performed by the optimization techniques, and so, among others, sequential experimentation seems to be an interesting candidate. A proposal could thus be to follow the 6 steps as described in table 1.

The main benefit of such an approach is the complementary aspects of the two methods. ARIZ (if considering ARIZ-85-C and the first part of ARIZ-85A for the analysis of initial situation) has one main goal: to focus on one key contradiction, the physical contradiction of the operating zone. To do so, resolver will have to limit its search for solution on the consideration of two resources (a tool and a product), one operating zone and operating time, and to describe the features this operating zone will have to satisfy in order to solve the problem. This technique is efficient because it fits the restriction of a human solver, human being only able to consider in the same time five (± 2) elements.

Sequential experimentation also fits the same goal, as the principal component analysis aims at limiting the number of considered parameters, the response surface method aims at localizing the area for the best solutions. So it seems promising to use the sequential experimentation to fulfill analysis of initial situation objectives and thus to identify the contradiction to consider for problem resolution.

Table 1. 6 steps approach to merge optimization and invention methods

Step	Objective	Method
1	Identify how many Action Parameters (AP) influence the Evaluation Parameters (EP)	Principal Component and Factor Analysis
2	Identify which AP influence each EP	Fractional Design of Experiments
3	Identify in the experimentation process the direction which will allow to move quickly towards an optimum	Factorial Design of Experiments with center-points
4	Locate the optimum solution if it exists	Response Surface method
5	If the optimum does not exist, extract the set of systems of contradictions from the final mathematical model	Generalized System of Contradictions
6	Solve the contradiction	OTSM-TRIZ techniques

2. Sequential experimentation

The proposed approach is based on the use of the following elements:

- Principal component analysis and factor analysis, which belongs to the family of multivariate analysis [1]. Multivariate analysis aims to reduce the data into a smaller number of components (few underlying factors).
- Factor analysis [2] is very similar to principal component analysis but design for a different purpose.
- Factorial designs allow for the simultaneous study of the effects that several factors may have on a process. When performing an experiment, varying the levels of the factors simultaneously rather than one at a time is efficient in terms of time and cost, and also allows for the study of interactions between the factors. Interactions are the driving force in many processes. Without the use of factorial experiments, important interactions may remain undetected.
- In a factorial experiment, responses are measured at all combinations of the factor levels, which may result in a prohibitive number of runs. For example, a two-level full factorial design with 6 factors requires 64 runs; a design with 9 factors requires 512 runs. To minimize time and cost, one can use factorial designs that exclude some of the factor level combinations. Factorial designs in which one or more level combinations are excluded are called fractional factorial designs. Fractional factorial designs are useful in factor screening as they reduce the number of runs to a manageable size. The runs that are performed are a selected subset or fraction of the full factorial design.
- Response surface methods [3] are used to examine the relationship between a response and a set of quantitative experimental variables or factors.

2.1. Principal component analysis

Taguchi [4] developed a method to enhance product quality, this method had great success to improve manufacturing products and processes. The Taguchi method evaluates product quality by applying the signal-to-noise ratio and, in doing so, the optimal factor/level combination obtained from the Taguchi method can be determined to reduce simultaneously the quality variation and bring the mean close to the target value. Despite its widespread industrial applications, the Taguchi method can only be used for optimizing single-response problems [5]. The Principal Component Analysis is then conducted on signal-

to-noise values to obtain a set of uncorrelated principle components, which are linear combinations of the original responses.

The main idea of Principal Component Analysis is to choose the axes maximizing the variance of the values representing the system [6]. Principal Component Analysis enable to find a new orthonormal coordinate system such that the variance of the projection of the data points on the first axis is the maximum among all possible directions, the variance of the projection of the data points on the second axis is the maximum among all possible directions which are orthogonal to the first axis, and so on.

Principal components analysis is commonly used as one step in a series of analyses when too many predictors relative to the number of observations are supposed. By analyzing the data covariance structure the data dimension can be reduced strongly.

2.2. Factor Analysis

The purpose of factor analysis is to reduce the dimensionality of a problem by exploring the correlation among its variables [7]. Factor analysis [8] identifies unobserved variables that explain patterns of correlations within a set of observed variables. It is often used to identify a small number of factors that explain most of the variance embedded in a larger number of variables. Thus, factor analysis is about data reduction. It can also be used to generate hypotheses regarding the composition of factors. Furthermore, factor analysis is often used to screen variables for subsequent analysis (e.g., to identify collinearity prior to performing a linear regression analysis).

Factor analysis is used to understand what constructs underlie the data. The two analyses, Factor Analysis and Principal Component Analysis, are often performed on the same data. For example, one can conduct a principal components analysis to determine the number of factors to extract in a factor analytic study.

2.3. Factorial Design of Experiments

Design of Experiments [9] is an organized method for determining the relationship between factors (process variables X_i) affecting a process and the output of that process (response variables Y_i). Experimental design is a strategy to gather empirical knowledge, i.e. knowledge based on the analysis of experimental data and not on theoretical models. In an experiment, one or more process variables (or factors) are changed in order to observe the effects these changes have on one or more response variables (outputs). The factors are controlled parameters, whereas the outputs are measurable ones.

One of the objectives of DoE is to obtain the most robust model with the minimum of experiments, which can be reached by the use of Taguchi's methods [10].

The factorial design method enables to estimate both the main effect and the interaction effects. The main effect refers to the effect caused by that changed factor, while the interaction effect refers to when the effect of one factor is dependent on the value of another factor.

2.4. Fractional Factorial Design of Experiments

Common methods to conduct performance evaluations are "one-factor-at-a-time" and exhaustive methods [11]. These ad hoc methods are engineering-based, where the engineers use their judgment to select test cases. The "one-factor-at-a-time" method evaluates the impact of each factor by varying one factor at a time, keeping all other factors constant. This method does not capture the interaction between factors. The exhaustive method tests all factors and all combinations of factors at all levels. This is a complete, but very costly approach. The latter two methods are sometimes used when the number of

factors is small. However, none of the methods are appropriate when many factors influence on the performance, due to the large number of test cases that would be required.

The fractional factorial design methodology originates from the planning and performance of experiments and is a subtype of factorial designs [9]. It supports the selection of cases to be investigated to enable analysis of the effect of different factors and combinations of factors. Several factors are varied at the same time in a factorial design, which is the main difference compared with a "one-factor-at-a-time" method.

A fractional factorial design is a type of factorial designs, where the number of test cases is reduced compared to a complete factorial design

2.5. Response Surface Method

Response surface methods [12] belong to a class of global optimization algorithms that retain all accumulated data about the objective function and use all of it to determine where next to evaluate the objective. They are particularly appropriate for problems where the objective is multimodal and expensive to evaluate, which is common in engineering applications; response surface methods are thus extremely important in the development and analysis of complex, real-world, deployed systems. Response surface methods have many free parameters that must be supplied by the user to tailor the method to the optimization problem at hand.

These methods are often employed after you have identified a "vital few" controllable factors and you want to find the factor settings that optimize the response. Designs of this type are usually chosen when you suspect curvature in the response surface. A response surface design helps to model the "Pareto-frontier" of a set of parameters

3. TRIZ based approach for problems of invention

3.1. OTSM-TRIZ principles

Initially OTSM-TRIZ was developed to extend the efficient application of Classical TRIZ to a variety of non-engineering fields, particularly the area of Education. Over the last few years OTSM-TRIZ has also been developed in the direction of dealing with problematic complex interdisciplinary situations.

OTSM-TRIZ is based on a set of axioms, a main axiom and auxiliary axioms [13]:

- The axiom of description, the main axiom defines that human solver use subjective models of objects to think. To solve a problem it is thus necessary to change the way the object is thought.
- The axiom of Impossibility says that a solver, to find a solution, first have to use descriptions that look impossible.
- The axiom of root of problems defines that any problem appears as a contradiction between objective laws that produced particular situation and the solver needs in this particular situation.
- The axiom of reflection reminds that during problem solving process, the solver has to stop and reflect on what was done before.
- The axiom of process defines that any element in the world should be considered as a process.
- The axiom of the world of unity defines the world as a unified system that exists according to general objective laws.
- The axiom of the world of disunity defines every system as a separate part, which exists according to particular objective laws.

- The axiom of connectedness between the world of unity and the world of disunity claims that general objective laws are connected to particular objective laws by the resources building the particular system.

3.2. Generalized System of Contradictions

The Generalized System of Contradictions, illustrated on figure 1, is the generalization of the OTSM-TRIZ system of contradictions [14] based on the use of concepts, which are defined as logical assertions about values of the parameters [15]. Two concepts based on a set of action parameters satisfy two sets of evaluation parameters. The desired result is then the simultaneous satisfaction of the two sets of evaluation parameters. This generic model satisfies the following equivalence “a contradiction exists if and only if no solution can be found by optimization of a known model”.

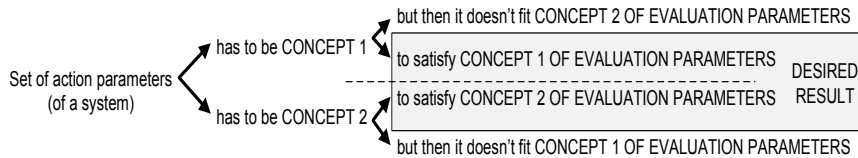


Fig. 1. Generalized System of Contradictions

As detailed in [16], similarities but also differences exist between the problem models of optimization approaches and General System of Contradictions. Even if the models in optimization approaches are not explicitly defined in order to state problems, it is quite compatible with the model of Generalized System of Contradictions. The analogy between these two kinds of models is quite evident, as defined in table 2. In the both cases, two categories of parameters are defined, those to evaluate the result and those to act on the system in order to reach the desired result.

Table 2. Comparison between optimization models and the GSC model

	Optimization models	Generalized System of Contradictions
System model	Controlled Parameters	Action Parameters
Result evaluation	Measured Parameters	Evaluation Parameters

So the extraction of GSC out of the models for optimization is not direct, but it is possible. Moreover the cross-fertilization of both approaches is quite obvious, described in table 1, a solution is search first of all through optimization approaches, if one is found the process is ended, otherwise the use of Generalized System of Contradictions is performed.

3.3. OTSM-TRIZ generic principles

The OTSM-TRIZ principles to combine opposite demands [17], i.e. to solve contradictions, are the generalization of classical TRIZ methods to separate the conflicting requirements for physical contradictions, enabling the application not only for technical problems.

8 principles have been defined to solve the contradictions when referring to any kind of problems, not just for technical problems:

- Separation of opposite properties at the Macro-level, in time, in space, or in other appropriate parameter. This principle acts as a separation at the sub-system level.
- Separation of opposite properties at the Micro-level, in time, in space, or in other appropriate parameter. This principle acts as a separation at the sub-system level.
- Separation of opposite properties between the System and Sub-system: the system has a property and the sub-system has the opposite property. This principle acts as a separation at the system level.
- Addition of opposite properties of System and Anti-system, then convergence. This principle acts as a separation at the super-system level.
- Separation of opposite properties by addition of new features to a property. This principle acts as a separation at the property level.
- Suppression of the opposition between properties by elimination of properties: deduction (imitation, LIKE something; IMAGE of something). This principle acts as a separation at the property level.
- Suppression of the opposition between properties by replacement or addition of another parameter. This principle acts as a separation at the property level.
- Suppression of the opposition between properties by modification of the reference value (Etalon). This principle acts as a separation at the value level.

4. From Sequential experimentation to generalized system of contradictions

A problem has been treated with the proposed approach in [18], but for confidentiality reasons, the name of parameters and the nature of the problem, as the results of the study won't be presented in this article.

4.1. Results out of the Multivariate analysis

The goal of principal components is to explain the maximum amount of variance with the fewest number of components. In the case, it has been observed that almost 100% of the total variation of all responses is associated to two parameters. However, one can observe in the correlation matrix that one component (PC1) have a positive relationship with the "evaluation parameter 1" and "evaluation parameter 2" but negative for "evaluation parameter 3" while the second component (PC2) shows the opposite behavior.

The Eigen value plot provides one method for determining the number of principal components. The scree plot displays the component number versus the corresponding Eigen value. The Eigen values of the correlation matrix equal the variances of the principal components. The score plot graphs the second principal component scores versus the first principal component scores. The ideal pattern is a steep curve, followed by a bend and then a straight line.

In the studied case, two components influence in majority the responses, as illustrated on figure 2.

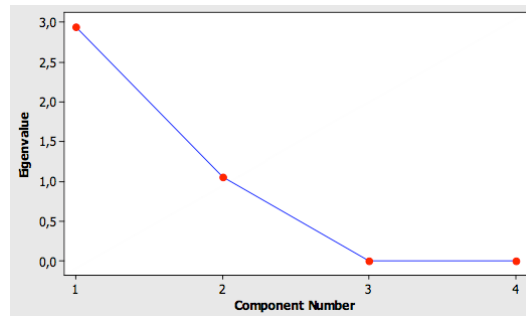


Fig. 2. Eigen Value plot of principal components

In a second step a factor analysis has been performed. This factorial analysis has been limited at three factors and confirms that only a few set of factors impacts the responses.

Then, the factor analysis has been used to assess the data structure and detect clusters, outliers, and trends. The findings can be represented in a graphical way by the biplot graph. The biplot overlays the score and loading plots. The second principal component scores are plotted versus the first principal component scores. The loadings for these two principal components are plotted on the same graph. The plot may reveal groupings of points, which may indicate two or more separate distributions in the data. If the data follow a normal distribution and no outliers are present, the points are randomly distributed around zero.

In the studied case one can observe that the two main factors load the responses in an asymmetric way. As represented in the biplot below (cf. figure 3), the first component influences largely EP1, while the second one seems to act on the EP2 potential.

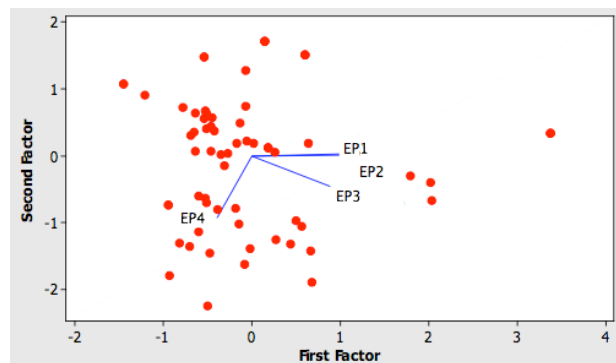


Fig. 3. Biplot for two main Principal Components

This representation points out that a conflict probably exists conflicts between the responses and the factors 1.

4.2. Design of Experiments

In order to find the critical factors that act on the two main principal components, the analysis of the impact of three action parameters has been performed with a 2level factorial plan.

The results, presented on figure 4, show a quite high explain ability rate of the model and demonstrate the impact of all factors.

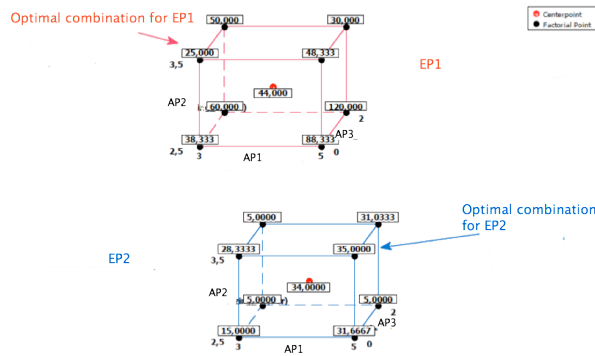


Fig. 4. Response cube plot of Design of Experiment

However there we could observe that even if the AP3 demonstrates the highest impact, it seems that a contradiction exists also on the AP1. Because the AP1 has to be low in order to satisfy EP1 and have to be high in order to satisfy as much as possible EP2 ; while AP3 have to be low to satisfy EP1 and high to meet EP2 expectations. However, the model shows a curvature which indicates that the effects of the AP1 on both characteristics in non linear.

4.3. From Design of Experiments to Generalized System of Contradictions

Out of the analysis of the Design of Experiments, some concepts could be formulated which enable an improvement of existing solution, but also which do not totally fulfilled the initially defined specs. From the previously conducted analysis one Generalized Contradiction could be formulated representing the main impact on the two main Principal Components on the Evaluation Parameters of the specs. This contradiction is reported on figure 5.

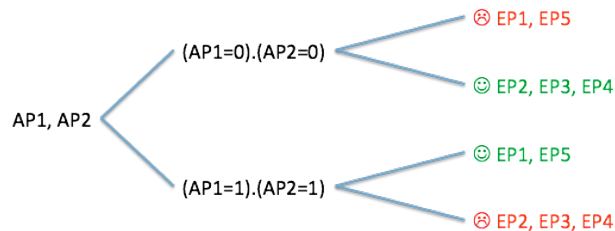


Fig. 5. Generalized Contradiction out of Design of Experiments

5. Conclusion

The article presented an approach combining both efficient optimization methods and methods of TRIZ when no solution can be found out of the application of optimization methods. In the study presented in this article improvements could be found out of the traditional approaches, but these solutions were recognized as compromises in regard of the initial set of objectives. So it was decided to

go further through the application of inventive methods, and much more interesting results were formulated this way.

Now this combined approach seem very promising, but still some questions have to be tackled:

- In the way the Design of Experiments is conducted, one of the objectives is to focus on a small set of action parameters, which enable a formulation of contradiction quite as similar with a “classical-TRIZ” system of contradictions. But the question is: is it a good hypothesis to focus on this small set, aren’t the missing information important in the problem model? What if it is not possible to focus on two or three Principal Components?
- One of the assumption on which the Generalized System of Contradictions is based is to know, for each Evaluation Parameter, at least one configuration satisfying it. But the way the Design of Experiments is conducted could also lead to the definition of surfaces in which this assumption is not respected. So, how to tackle such situation, has the Generalized System of Contradiction model to evolve? Or does it point out that in the model of the Design of Experiments some important information (range of values or Action Parameter) is missing?

Now other applications of this approach will be conducted to reinforce the validation of its usefulness and also to answer the two previously elicited questions.

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