COMPARISON BETWEEN EXPERIMENTATION AND MULTIPHYSICS MODELLING TO IDENTIFY PRIORITY CONTRADICTION

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ABSTRACT

The contradictions of TRIZ are now widespread and recognized as an effective inventive design tool. They make it possible to find solution concepts to problems that cannot be solved by optimization approaches. However, many contradictions could be formulated and it could be difficult to choose the priority one. The authors propose here two methods to formulate the contradictions and identify the priority contradiction: an experimental approach on the one hand, and a multiphysics approach on the other hand. This analysis, illustrated through an example of 3D printing of parts, shows that these two approaches are similar in terms of result, and indeed make it possible to formulate contradictions taking into account all the complexity of a system.

Keywords: Creativity, Optimisation, Design methods, Case study

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1 INTRODUCTION

Einstein is reported to have said that if he had one hour to solve a problem, he will take 55 minutes just formulating it. Indeed, clarifying a problem could be seen as, at least as important, if not more, than solving it (Dewey, 1939, Simon, 1973). And then, formulating the problem that has to be solved, different ways to solve it can be considered. Optimizing a system means searching for the best values for the different parameters of a system, in regard of the specs. In the contrary, inventing a new system means modifying the considered system, by the addition of new parameter, or by modifying the nature of the relationships between the parameters. When starting the design process, it is not possible to know a priori if the specs could be satisfied by optimization approaches, then in (Dubois et al., 2015), a method to make a continuum between both approaches has been proposed, based on TRIZ methods as inventive ones. This means that the problem, if not solved by optimization approaches will be formulated as a contradiction. But many contradictions could be formulated (Lin et al., 2014), and the question remains about the choice of the priority contradiction to consider.

Several approaches exist to point out this priority contradiction, either based on the weight of design parameters on the satisfaction or not of the specs (Rousselot et al., 2012), but this weight is generally based on human experts' opinion; or based on a root cause analysis to highlight the origin of the problem (Souchkov, 2010). But these approaches are quite cartesian, analysing a linear chain of causes, and thus are not able to consider the complexity of a system, and all the inter-relationships between all the design parameters.

In this article, the authors aim at exploring two ways to formulate and choose the priority contradiction, an experimental approach based on Design on Experiments, and a more formal one, based on the formulation of multiphysics equations. The objective is to present these two approaches as they tackle both systems in their whole, and then to compare them, in order to help in choosing which one is the more relevant.

The first part of the article will present the pattern of System of Contradictions and of its generalization. Then the second part will be dedicated to describe Design of Experiments and one of the tool for relationships characterization, the Main Effects Plot. Then, an example will be described, related to the realization of 3D-printing parts and aiming at maximizing its mechanical properties and minimizing the printing time. The two proposed approaches to identify the priority System of Contradictions will be illustrated and compared. Then some conclusions and perspectives will be presented.

2 SYSTEM OF CONTRADICTIONS

2.1 Classical TRIZ system of contradictions

In TRIZ, one of the main pattern to model the problems is the one of contradictions. In border of what is called classical TRIZ (TRIZ as has been defined by G. Altshuller), three models of contradictions have been defined: administrative, technical and physical contradictions (Altshuller, 1984). The administrative contradiction is only the recognition that no solution is known to satisfy the objectives of the considered problem. The two other ones (technical and physical) propose tools to solve the formulated contradiction. Whereas the technical contradiction points out the non-compatibility of two Evaluation Parameters (EP), specs of the problem, the physical contradiction elicits one specific design parameter (called Action Parameter, AP) that must be in two different states in order to satisfy the contradictory Evaluation Parameters. The link between these two models of contradictions has been clarified in (Khomenko et al., 2007), as illustrated in figure 1, in a so-called System of Contradictions (SoC).

This link is important as it enables the clarification of the reason why some configurations of a system better satisfy the specs. Indeed, it elicits the influence of an Action Parameter on the Evaluation ones. So, it is a way to better point out means to act on the problematic situation if aiming at satisfying the two EPs implied in the SoC.

2.2 Generalized system of contradictions

In (Dubois et al., 2009) the authors presented the generalization of this SoC, to satisfy the equivalence of the existence of a problem and of a formal contradiction. Indeed, with the previously presented SoC, a solution of the Technical Contradiction (based only on two EPs) can exist whereas no solution is known if considering all the specs, based on more than two EPs. This Generalized System of Contradictions (GSC, as illustrated on figure 1) also highlights more explicitly the link between the APs and the EPs, as any configuration of a system could be represented as a state of APs considered in a Generalized Physical Contradiction. In (Chibane et al., 2021) the authors also illustrated how this model of GSC enable to automatically extract contradictions out of table of influences.

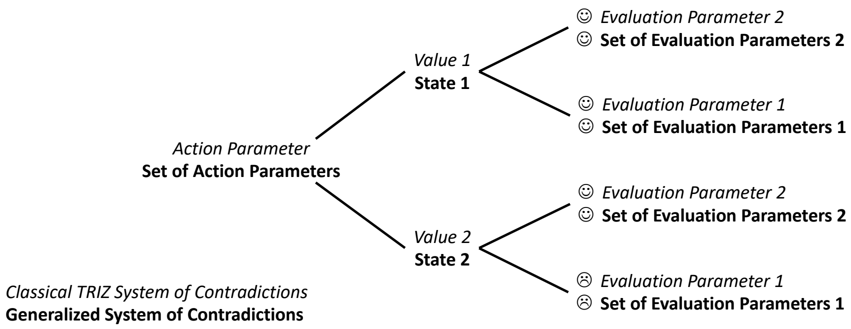

Figure 1. Classical TRIZ and Generalized System of Contradictions

These Systems of Contradictions then clarify the means to act on a system when trying to satisfy different contradictory specs. The benefits of the generalized model has been clarifies in (Lin et al., 2013) but also the fact that a huge number of GSC could be formulated for a given problem. Thus the question of the priority problem to consider arises. In this article the question of this priority GSC will be considered as identifying the GSC that implies the maximum number of EPs, and the most influential AP.

3 DESIGN OF EXPERIMENTS ANALYSIS

3.1 Design of experiments

Experimental modelling first appeared between 1920 and 1930 thanks to the research work of the pioneer of statistics, Mr. Ronald A. Fisher. He demonstrated that flaws in the way the experiment that generated the data was performed often hampered analysis of the systems data.

Fisher systematically introduced statistical thinking and principles into designing experimental investigations, including the factorial design concept and the analysis of variance. His two books (Fisher, 1958, Fisher, 1966) had profound influence on the use of statistics, particularly in agricultural and related life sciences.

Fischer's work has been analyzed and expanded by George Edward Pelham Box (Box, 1978). A second important phase of experimental modeling begins with the introduction of the "response surface methodology" (RSM) to the industrial world by Box and Wilson (Box and Wilson, 1951).

In recent years, RSM and other experimental modeling techniques have spread in industry mainly in research work of Box and more recent in (Box and Draper, 2007, Box et al., 2005).

In parallel with the development of these statistical analysis methods, studies have been carried out to better organize the experiments and to optimize the number of experiments according to the desired results and the work on optimal design of experiments (DOE) began.

Design of Experiments (DoE) is a powerful data analysis tool that allows the understanding and study of different complex processes, the use of a DoE also makes it possible to reduce the number of experiments necessary for understanding the process. (Kiefer, 1961) proposed a formal approach to selecting a design based on specific objective optimality criteria. The work of Genichi Taguchi and Wu (1979), Kackar (1985), and Taguchi (1986) have a significant impact on the development of DOEs. Taguchi suggested highly fractionated factorial designs and other orthogonal arrays along with some novel statistical methods to solve these problems.

DOEs are a powerful tool for analyzing the influence of process variables on specified properties. Appropriate data can be analyzed by statistical methods such as RSM and multiple linear regression analysis. The experimental data can be fitted using a second-order polynomial response surface model as expressed in Equation (1).

$$Y = \beta_0 + \sum_{i=1}^{N} \beta_i X_i + \sum_{i=1}^{N} \beta_{ii} {X_i}^2 + \sum_{i \neq j}^{N} \beta_{ij} X_i X_j + \omega \qquad (1)$$

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Where Y is the predicted response, the parameter β_0 is the model constant, β_i is the linear coefficient, β_{ii} is the quadratic coefficient and β_{ij} is the cross-product coefficient. X_i and X_j (i<j) are the independent variables that are known for each experimental run. ω is the experimental error term.

3.2 Main effects plot

An important tool in the analysis of experimental designs is the main effects plot, this is a plot of the mean response values at each level of a design parameter or process variable. One can use this plot to compare the relative strength of the effects of various factors. The sign and magnitude of a main effect would tell us the sign of a main effect, that is, whether the average response value increases or decreases. The magnitude tells us of the strength of the effect. If the effect of a design or process parameter is positive, it implies that the average response is higher at a high level rather than a low level of the parameter setting. In contrast, if the effect is negative, it means that the average response at the low-level setting of the parameter is more than at the high level

Figure 2 illustrates the main effect of the filling rate and number of fiber layers on the printing time for a 3D printing process. One can see from the figure, that the printing time increases when the filling rate setting varies from low to high (i.e. 50 to 100), and the same for the number of fiber layers.

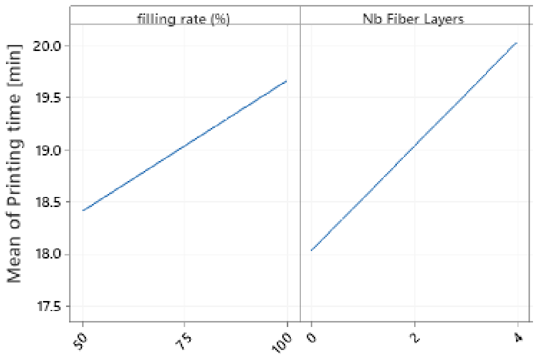

Figure 2. Main effect plots example

The effect of a process or action parameter can be mathematically calculated using the following simple equation 2:

$$Ef = \bar{F}_{(+1)} - \bar{F}_{(-1)} \tag{2}$$

where $\bar{F}_{(+1)}$ is the average response at high-level setting of a factor, and $\bar{F}_{(-1)}$ is the average response at low-level setting of a factor.

An interactions plot is a powerful graphical tool which plots the mean response of two factors at all possible combinations of their settings. If the lines are parallel, this indicates that there is an interaction between the factors. Non-parallel lines are an indication of the presence of interaction between the factors.

4 IDENTIFYING THE PRIORITY GSC

The example that will be taken to illustrate how a link can be done to make a continuum between optimization analysis and inventive problem resolution will be based on analysing the benefits of fiber reinforcement parameters on the final mechanical properties and printing time of FDM 3D printed samples. The piece to produce is made of Onyx (a nylon material reinforced with chopped carbon) defined by a specified shape and volume (as illustrated on figure 3). Four kind of CFT have been considered: carbon, Kevlar, glass, and HSHT glass.

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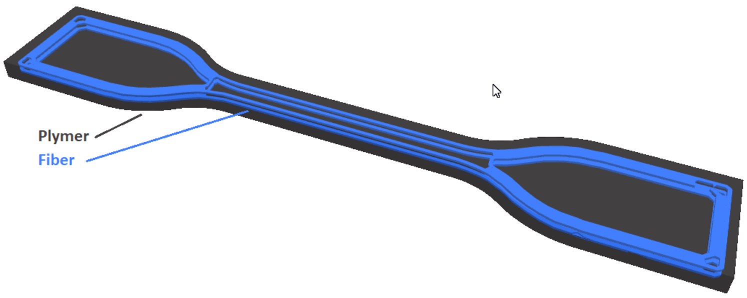

Figure 3. Piece of Onyx to be analyzed

The objective here is to illustrate how the link between Action Parameters and Evaluation ones can be elicited and thus lead to the formulation of GSCs. A second task is to help in identifying the priority GSC, that has to be considered for resolution. Two approaches will be considered and compared: an experimental one based on Design of Experiments, and a multiphysics one.

4.1 Design of experiments and main effects plot analysis

Design of experiments (DOE) enables to investigate relationships between inputs and observed outputs. In the presented case a full factorial design has been realized in order to define how many experiments were necessary for the 3 inputs - infill density (ID), continuous fiber type (CFT) and number of fiber layer - and the 6 outputs - Young's modulus (E), ultimate tensile strength (σ), elongation (A), weight (ω) and printing time (PT). The chosen values for the input are detailed in Table 1.

Table 1. Values of inputs for the design of experiments

Infill density (ID)	Continuous fiber type (CFT)	number of fiber layer (NFL)
50%	Carbon	0
100%	Kevlar	2
	Glass	4
	HSHT glass	

A set of 24 experiments have been conducted, and the result is illustrated on table 2.

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Table 2. results of the DoE, with the satisfying values in green

	Action Parameters			Evaluation Parameters				
Exp. N°	filling rate (	Nb Fiber La	Fiber Type	Printing tim	Weight [g]	Elongation	Youngs mo	Tensile strength [MPa]
1	50	0	No Fiber	17	1,22	3,85	1,42	31
2	50	0	No Fiber	17	1,22	3,90	1,26	26
3	50	0	No Fiber	17	1,22	3,80	1,60	37
4	50	2	Carbon	17	1,46	0,75	2,73	69
5	50	2	Kevlar	19	1,37	0,94	1,50	10
6	50	2	HSHT Fiberg	20	1,38	1,50	1,57	63
7	50	4	Carbon	17	1,48	0,75	4,08	111
8	50	4	Kevlar	20	1,4	0,99	2,27	80
9	50	4	HSHT Fiberg	21	1,43	1,60	2,05	98
10	100	0	No Fiber	19	1,52	8,00	1,25	43
11	100	0	No Fiber	19	1,52	8,00	1,28	42
12	100	0	No Fiber	19	1,52	8,00	1,33	43
13	100	2	Carbon	17	1,52	0,72	2,73	14
14	100	2	Kevlar	20	1,52	1,00	1,83	41
15	100	2	HSHT Fiberg	21	1,53	1,60	1,98	77
16	100	4	Carbon	18	1,54	0,73	4,24	114
17	100	4	Kevlar	21	1,52	0,99	2,32	17
18	100	4	HSHT Fiberg	22	1,56	1,50	2,08	94
19	50	0	No Fiber	17	1,22	3,85	1,43	31
20	50	2	Fiberglass	19	1,38	1,50	1,35	20
21	50	4	Fiberglass	20	1,43	1,40	2,07	88
22	100	0	No Fiber	19	1,52	8,00	1,28	42
23	100	2	Fiberglass	20	1,53	1,40	1,37	32
24	100	4	Fiberglass	21	1,56	1,60	1,96	96

One can easily recognize, in Table 2, that no ideal solution was found (satisfying the best value for each of the Evaluation Parameter), then the question to find a concept enabling to overcome the Pareto frontier was tackled, by considering the GSC representing the limits of the system. To do so the consideration of the main effect plots analysis was conducted.

The Main effect plots analysis has been conducted to identify the way each A.P. influences the E.P.s. The effect on Elongation is illustrated on figure 4. As the objective is to maximize this elongation, one can easily recognize that the filling rate has to be maximize whereas the number of fiber layers has to be minimized, and the type of fiber seems to have little influence on this E.P..

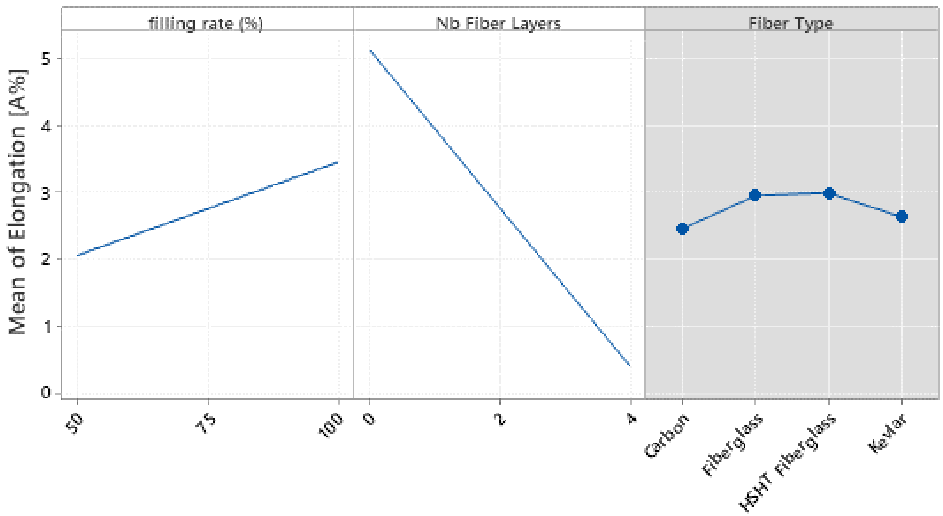

Figure 4. Main effect plots for Elongation

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On table 3, all the identified influences, out of the main effects plots have been summarized. A blank cell in the table means that no real influence of the A.P. can be recognized.

Table 3. Results of the main effects plots analysis

		Evaluation Parameters				
		Printing time [min]	Weight [g]	Elongation [A%]	Youngs modulus [GPa]	Tensile strength [MPa]
Action Parameters	filling rate (%)	**-**	**-**	**+**		
	Nb Fiber Layers	**-**	**-**	**-**	**+**	**+**
	Fiber Type	**Carbon**	**Kevlar**		**Carbon**	**Kevlar**
	-	A.P. has to decrease to satisfy E.P.				
	+	A.P. has to increase to satisfy E.P.				
	Carbon	Specify the fiber type to satisfy E.P.				

The table 3 highlights that one System of Contradictions could be interesting to consider, the one based on the number of fiber layers, as illustrated on figure 5. The choice of this GSC relies on the fact that this GSC implies all the EPs, and moreover that the Number of fiber layers is the most influential Action Parameter.

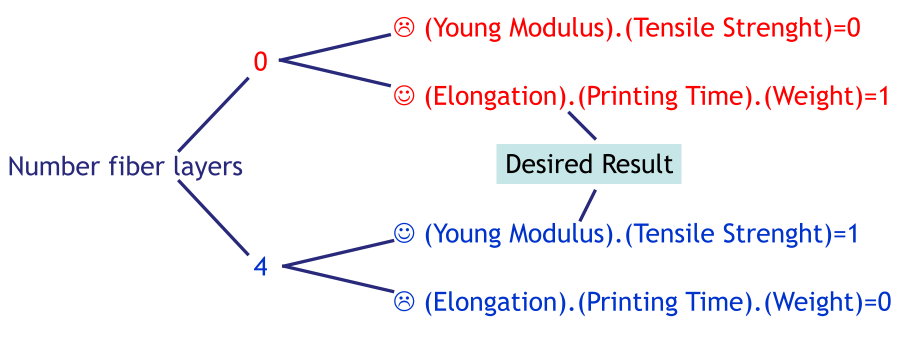

Figure 5. GSC extracted from the main effect plots analysis

4.2 Multiphysics analysis to extract the priority GSC

An alternative approach has been considered, to compare the results in regard of trying to avoid the realization of experiments. To do such multiphysics analysis, it has been necessary to identify first, the mean to act on the formulated set of Evaluation Parameters, then to search for the equations governing the behavior of the identified parameters.

For example, if trying to model the multiphysics equation for the printing time (t_{part}), it will imply the consideration of the volume of the piece (v_{part}), of the volume of the printed fiber (v_{fiber}) and also the flow rates of the polymer (Q_{poly}) and of the fiber (Q_{fiber}), as presented in equation 3:

$$t_{part} = \frac{(v_{part} - v_{fiber}) * ID}{100 * Q_{poly}} + \frac{v_{fiber}}{Q_{fiber}} \tag{3}$$

Based on the elicitation of the multiphysics equations, a set of intermediary parameters has thus been identified, as have been characterized the influences between all the parameters. This enabled to build, as has been detailed for qualitative data in TFC21, a network of parameters, which is presented on figure 6.

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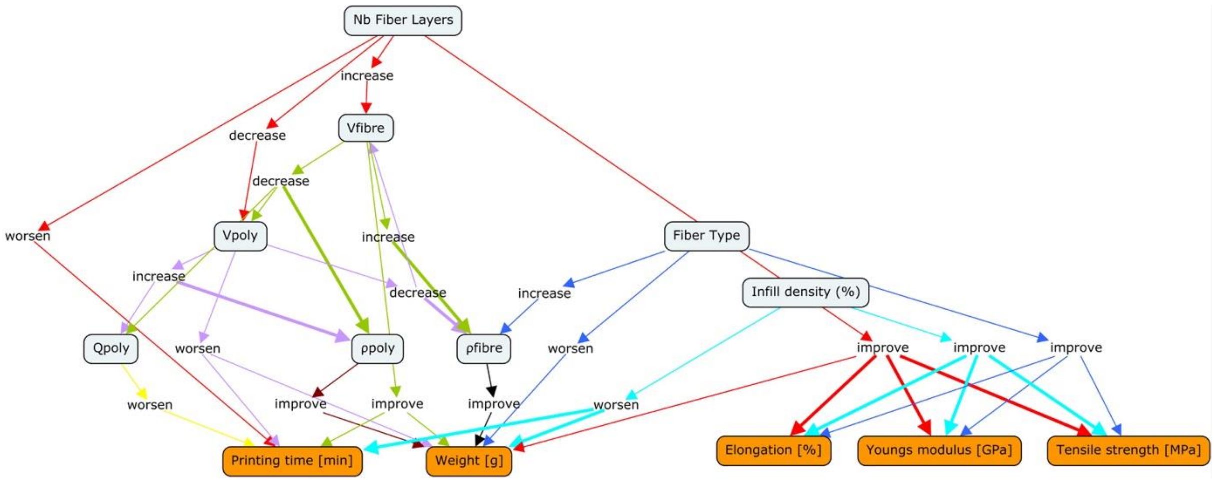

Figure 6. Network of parameters for the multiphysics analysis

This Network of Parameters also highlights the most influential Action Parameter as being the number of fiber layers, the same conclusion than with the Main Effects Plot analysis.

4.3 Comparative analysis

The two proposed approaches, based on experimentations and on multiphysics modeling lead to the same priority Generalized System of Contradictions. This is quite reassuring, as it shows that both approaches are coherent, even more can be complementary. Then the question arise of which approach is the more relevant when facing a new problem? As both seem to highlight the same priority contradiction, the choice can be made in regard of available resources. In regard of the cost of the required experiments on one hand, and on the easiness to build the multiphysics model on the other hand, one can choose the approach that is the more convenient in accordance with these specific conditions.

5 CONCLUSION AND FUTURE WORK

The objective of this article was to compare two different ways to formalize the priority problem to consider when facing inventive design. The authors aimed at clarifying the importance of the influence relationships between the parameters modelling a system, and how the characterization of the weight of these influences can help in choosing the priority problem. The proposed approaches are based on the use of TRIZ contradictions patterns to formulate the problems. The interest of these patterns is that they enable an efficient search of concept solution, once the problem is clearly formulated.

In this article the two proposed approaches differ by the way these influence relationships are highlighted, either through an experimental approach and the analyse of the Main Effects Plot, either through the definition of multiphysics models.

The results show that both proposals aim to similar results, which could be obvious if considering the way DoE have been defined, but which tackled questions as it was clear that the list of Action Parameters considered in the definition of the DoE was not exhaustive, and the example showed indeed that intermediary parameters have been considered. The benefits of the graphical representations of the Network of Parameters have been illustrated in (Dubois et al., 2021), based on the collect of data from experts' interviews, and thus for much more Action Parameters.

The fact that the choice between experimentations or multiphysics modelling relies only on the availability of knowledge for modelization, or on the cost of experimentations, tend to prove that the formulation of GSC and the choice of the priority one, based on any kind of influence table, could be performed.

In this article, both qualitative and quantitative parameters have been considered, this situation was quite easy to manage here, as the impact of the nature of the fiber was quite clear, but this point could lead to difficulties to manage situations in another context. Then the authors will consider now how to treat influence relationships for qualitative parameters.

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