Graphical support adapted to designers for the selection of an optimal solution in Design by Shopping

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GRAPHICAL SUPPORT ADAPTED TO DESIGNERS FOR THE SELECTION OF AN OPTIMAL SOLUTION IN DESIGN BY SHOPPING

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Abstract

Design space exploration, that is an embodiment of a paradigm Design by Shopping, refers to the systematic activity of discovery and evaluation of the elements in the design space in order to identify optimal solution by reducing the design space toward an area of performance. This activity is composed of three main phases: the discovery, the optimization and the selection. There are existing tools for the design space exploration with different graphs (ScatterPlot matrix, 2D and 3D scatter plot, parallel coordinates plot, etc.). These graphs are useful for the representation of multidimensional set of data with an unlimited number of alternatives (design points). Obviously, during the selection phase, designers face to a reduced design space with a limited number of design points (in a performance area). Thus, in our work, we try to identify which graph is the most adapted to the selection phase. It emerges, from literature, three graphs useful for the representation of multidimensional set of data (>3 variables) and with a limited number of alternatives (<50). Thus we have designed experimentation composed of 3 scenarios (with 13 design parameters and 5 variables of performance) performed by 30 participants. It results one graph more suited to the selection phase in the Design by Shopping: the Parallel Coordinates Plot.

Keywords: visualization, Computer aided design (CAD), Decision making

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1 INTRODUCTION

In engineering design, once the design has been formalized, a necessary design task is to make a selection from amongst candidate designs or parametric values (Otto & Antonsson, 1993). It can be in the preliminary concept phase, where the designer has to choose one solution over other alternatives, or in the detailed design where the designer has to choose particular values to use in a design model. The main challenge when designing complex systems (eg. cars, aircraft, etc.) lies in resolving the inherent trade-offs that exist between the overall system and subsystems, and between conflicting and competing objectives.

In the design space exploration the design selection is performed following the discovery and evaluation of the elements in the design space in order to identify optimal solution by reducing the design space toward an area of performance. In this method, visualization techniques are used as decision support tools. Graphs are useful for quickly visualizing the feasible solutions as opposed to impractical solutions, as well as those violating engineering constraints or client requirements. Three different situations can be represented with more or less data:

- Representing the single vector of design parameters featuring the product solution, (X), this refers to the feasible design space,
- Representing the single vector of solution performances for feasible solutions, (Y), this refers the feasible performance space,
- Representing two sets of design parameters and corresponding performances for feasible, $\begin{pmatrix} X \\ Y \end{pmatrix}$, this refers to the feasible design and performance space.

Graphical supports are effective for design parameters, engineering optimization (Barron et al., 2004) and conceptual design (Yannou et al., 2005). There are already many works in visual design and it has already been shown that fast graphical design interfaces impact user performance in terms of design efficiency, design effectiveness and the design search process (Ligetti et al., 2003). There are existing tools for exploring the design space with different graphs, namely:

- The ARL Trade Space Visualizer (Stump et al., 2004) is used to visualize on the same graph both the design parameters and performance variables with Scatter Plot Matrix, Parallel Coordinates Plot and Bar Charts.
- The VIDEO tool (Kollat & Reed, 2007) is used to separately visualize on two graphs the objective space (ie. performance variables) and decision space (ie. design parameters) with the 3-D Scatter Plot using color and size glyphs.
- The LIVE tool (Yan et al., 2011, 2012) is, on the one hand, used to visualize in two graphs, the input variables (design parameters) on one side and the output variables (performance variables) on the other. On the other hand, a tree structure is displayed. It represents the classification of input variable combinations. Both spaces (input/output) are projected in a 2D Scatter Plot in which color and shape glyphs (cluster creation) can be added. The tree structure is presented in a Treemap (Shneiderman, 1992) in which each node corresponds to an input attribute with a splitting value. Each leaf of the tree specifies the expected output value (with color scale), as a consequence of the particular input values described by the path from the root to that leaf.

In fact, these graphs are useful for representing multidimensional sets of data with unlimited numbers of alternatives (design points). Exploring the design space consists of three main phases: discovery, optimization and selection. During the selection phase, designers face a reduced design space with a limited number of design points (in a performance area). Which graphs allow designers to select an optimal solution during the final phase of the design process? (Cf. figure 1)

We know that exploring the design space is the embodiment of a paradigm where designers shop for the best solution. It is called Design by Shopping and was coined by Balling (Balling, 1999). Indeed, Balling (Balling, 1999) noted that the traditional optimization-based design process to "formulate the design problem, obtain analysis models and execute an optimization algorithm" leaves designers unsatisfied. Designers like consumers want to "shop" to gain an insight into trades, feasible and impractical solutions, and to learn about their alternatives before making decisions. Design by Shopping, firstly, allows designers to explore the design space, and, secondly, optimize and choose an optimal solution from a set of possible designs, and then develop realistic expectations with regard to what is possible.

So, in Design by Shopping, the selection phase should be supported by graphs that allow designers to observe all the design alternatives, therefore enabling them to distinguish between right and wrong responses. The graph should allow differentiation between design parameters and performance variables. With graphs, the designer needs to compare candidates according to criteria. In this way, the graph should help the designer find a so-called "optimal" solution. In this sense, it should not create confusion or add a load to the designer.

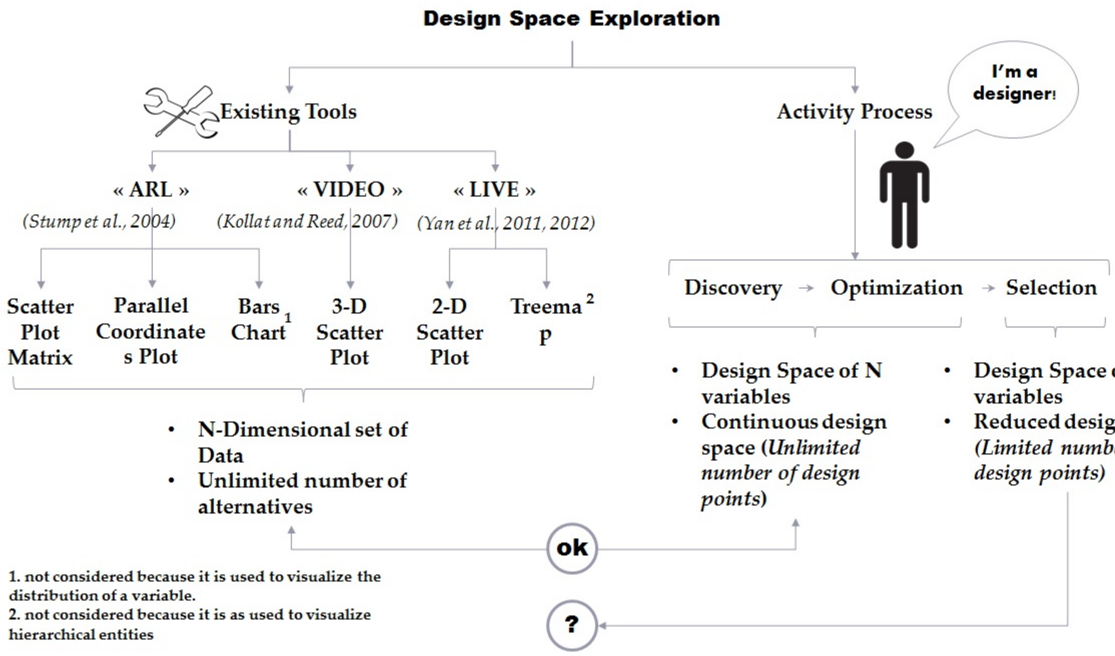

Figure 1. From Design Space Exploration to research question

We have thus identified three graphs useful for representing multidimensional sets of data (>3 variables) and with a limited number of alternatives (<50): Combined Table (CT), Parallel Coordinate Plot (PCP) and Radar Chart (RC). We carried out experiments with 30 participants and designed 3 scenarios to mimic the design activity. The framework was simplified in order to focus our study on the selection phase (13 design parameters and 5 performance variables where it is necessary to achieve trade-offs between conflicting objectives). We identified a graph more suited to the selection phase in design by shopping: the Parallel Coordinates Plot (PCP).

2 GRAPHS FOR THE SELECTION PHASE

In our context of achieving trade-offs and selecting an optimal solution, several graphs (design space representations) are available to us. As already mentioned, this is a case-representation of multidimensional sets of data with limited numbers of alternatives (design points). Based on the work of Miettinen (2014) and Keim (2000) (amongst others) about graph characteristics, we identify the values table, the table with heatmap, the combined values-heatmap table, radar chart and parallel coordinate plot (PCP). Gettinger et al. (2013) have already compared the values table, the heatmap and the PCP for multicriteria decisions and they conclude that it is necessary to check the efficiency of the combined values-heatmap table. Also, these authors do not consider the radar chart in their work. Thus, we propose comparing the three following graphs to select an optimal solution (design decision) in design space exploration: the Combined Table (CT), the Radar Chart (RC) and the Parallel Coordinates Plot (PCP). The interactive graphs are available at the following address: http://these.aaa.alwaysdata.net/expe1/

2.1 Combined Table (CT)

The Combined Table is a combination of table values and a table with heatmap (Figure 2 a.). In our implementation, each row is a design point (or alternative) and each column is a variable (or component). The interaction with the graph takes place on labels at the top of each column. By clicking on these labels, the values in the columns are sorted from highest to lowest. In addition to the values in the table, we added a heatmap. Theoretically, heatmaps are matrices in which the cells are colored according to their values. We already showed in (Abi Akle et al., 2013) that the most efficient visualization for a decision maker would be a monochromatic heatmap in red. In each column, the highest value has a bright red cell. The cell is white for the column's lowest value (color scale red-white). In addition, on mouse over, the entire row of values (corresponding to an alternative or possible solution) is underlined and the alternative's title appears at the top left of the interface. This representation is particularly useful for identifying patterns such as correlations (Cook et al., 2007).

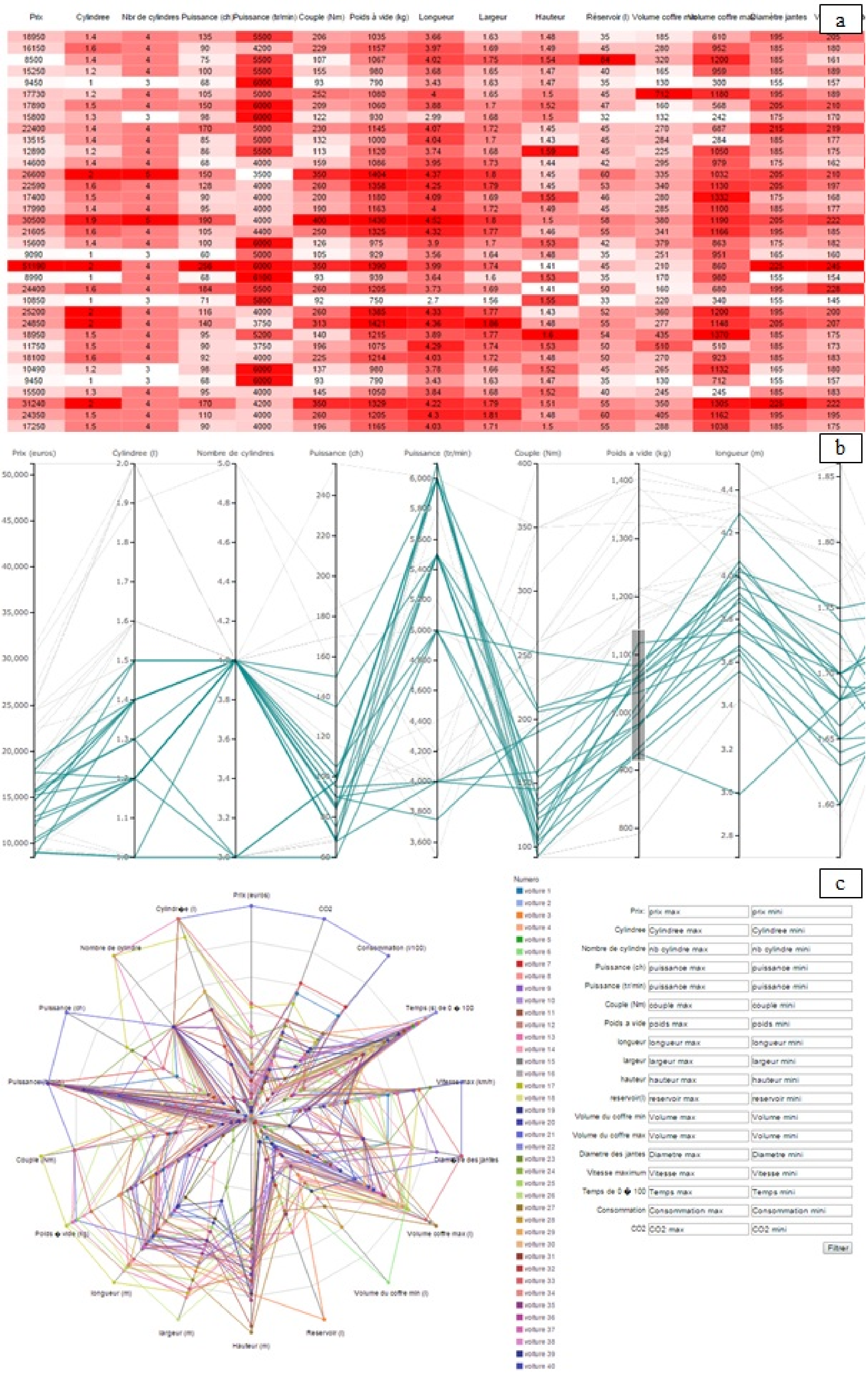

Figure 2. Screenshots of Combined Table (a.), Parallel Coordinates Plot (b.) and Radar Chart (c.)

2.2 Parallel Coordinates Plot (PCP)

Parallel Coordinates Plot is defined as a graph displaying multiple criteria without drastically increasing the complexity of the display (Inselberg, 2009). In PCP, variable values are displayed on separate axes laid out in parallel. The design points (or alternatives) are depicted as profile lines that connect points on the respective axes. According to Gettinger et al. (2013), this representation can be readily interpreted and provides a good overview. Furthermore patterns such as positive, negative and non-trivial (multiple) correlations may quickly be identified at a glance. In our implementation, the interaction is directly applied on the graph. To filter the values, simply place the mouse on one of the axes and, with a click, drag the cursor to obtain a desired range of the criteria like a window outside which value vectors are excluded. Also, the mouse, when moved above a line, is used to display the title of the design point (or alternative) at the top left of the interface (Figure 2 b.).

2.3 Radar Chart (RC)

In a Radar Chart, variable values are displayed on separate axes laid out in a concurrent radial manner (Figure 2 c.). As with PCP, the design points are depicted as profile lines that connect points on the respective axes. In our implementation, interactions are achieved by the mouse first on the points (on the axes) displaying the variable value and second on lines displaying the title of the design point (alternative). The filter action is done using a form. We chose to use a form so as to not overload the graph. In the field of health care (Saary, 2008), radar charts are seen as a form of powerful graph to effectively convey meaning in multivariate data.

3 EXPERIMENTAL DESIGN

To answer our research questions, we conducted a controlled experiment that adopted a within subject approach. Each participant performed the experiment on three graphs tested consecutively. To diversify the participant selection process, we propose an experiment that is based on three scenarios leading to the selection of one alternative in a car-choice problem. The three scenarios have been imagined to mimic the design activity in a simplified framework in order to focus on the selection phase of the design process. Scenarios are designed as brief marketing in which a profile target is described. For the three scenarios trade-offs between conflicting objectives have to be achieved in order to select an alternative, ie. choose an ideal in a car purchasing situation according to the scenario.

3.1 The three scenarios

We designed the Power scenario, Size scenario and Journey scenario. The three scenarios are defined by:

- "Size" Scenario: The target user has a family of three children and a spouse. They work all day long in a big city where it is difficult to park. That is why you should select one car that is as small as possible in order to be able to park easily (*width* and *length*) but with sufficient internal volume for the target user and his/her family (*height*, *trunk capacity* and *Trunk(max-min) capacit*y)
- "Power" Scenario: Looking for the most powerful car. The maximum *speed* of the vehicle must be as high as possible with the greatest *acceleration* (time to drive from 0 to 100km/h). The car should also have a large *horsepower* and significant *motor torque*. Finally, to ensure the car is as powerful as possible, you choose a car that is light (*weight* of the car).
- "Journey" Scenario: The target user is someone who travels almost every weekend with his/her car. You therefore look for a car with a big *tank* and minimum *consumption* because the target user doesn't want to stop often on the way to refuel, which would make the trip too expensive. Comfort is also an important factor: the car must be large (*width* and large *trunk*) and finally, a car with good handling should be selected (maximum *rim diameter*).

The data used in each graphical representation is the same ie. 40 cars and 18 variables ie. 13 design parameters and 5 performance variables for each problem scenario (italic text in the scenario descriptions). The 18 variables are as follows: price, engine size, number of cylinders, horsepower, power (rpm), motor torque, weight (of the car), width, length, height, tank, trunk (max. and min.) capacity, rim diameter, maximum speed, acceleration (time to drive from 0 to 100km/h), fuel consumption and CO_2 emissions. The cars' names have been erased and replaced by a number (ranging from 1 to 40). Data is gathered from real cars. In order to obtain a wide range of data, we have chosen cars from different categories (large 4x4 and small city car).

3.2 Procedure

The experiment is divided into three main steps (see Figure 3). The first step begins with a presentation of the experiment's objectives and a preliminary questionnaire in order to obtain subject profiles and their pre-existing knowledge for the graphs tested. The second step is the main part of our experiment and consists of testing the 3 graphical supports after a short training course. In this part, we ask the participant to read the scenario description, to "play" a role (as described in the scenario) and to use the graphic tool to deduce a single solution. We call the chosen solution a "trade-off" because the scenarios are designed with five conflicting objectives. It is therefore necessary to reach a trade-off. The training course is about finding the needed item (car) as well as interacting with graphs. The third step is a questionnaire with the aim of collecting subjective measurements (participant effort, confidence, etc.).

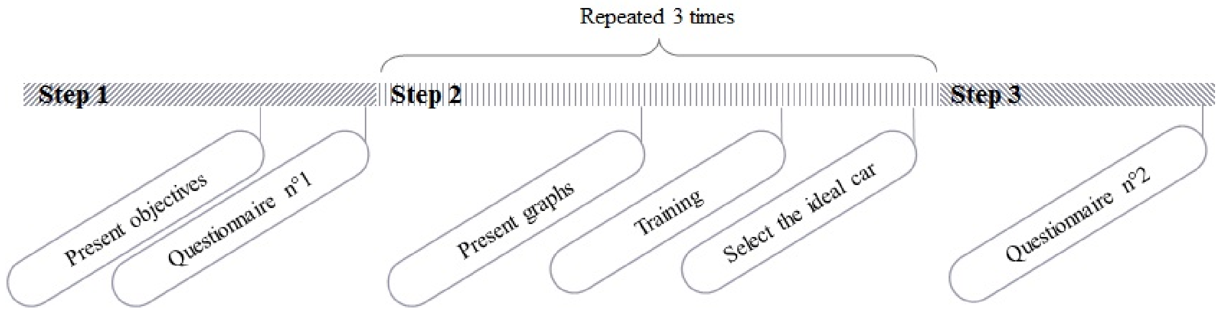

Figure 3. Illustration of the procedure

The total time for a complete session is about 1:10 (ie. 35h of experiments over 4 weeks). It is worth noting that for step 2, in order to avoid the effect of rank and order induced by the graph's sequence, we use the counterbalance method. In our case, this means different graphic sequences (eg. PCP – RC – CT, PCP – CT – RC, CT – PCP – RC, etc.). In addition, this method allows scenarios for testing graphics and balancing the effect of participants' learning to be alternated.

3.3 Participants

Subjects were recruited from various teams of scientists in our research building (from various fields: engineering design, mechanical, electronic, computer, etc.). All subjects were voluntary participants. The 30 subjects carried out the experiment on the three graphic supports (PCP, CT, RC). Thus, we obtained 30*3=90 test results (the experiment respects a within subject approach). The mean age of the subject is 30.9 years (SD=7.3). The gender distribution is 53.3% women and 46.7% men. We observed that only 3.3% of participants had already used a PCP, 66.7% a Radar Chart and 33.3% a combined table.

4 MEASUREMENT

In our work, variables were either measured during the tests with the CamStudio[1] tool or collected through the final questionnaire (n°2).

4.1 Variables measured

The influence of the graph on trade-off assessment is measured with two variables: the time spent on decision-making (ie. selecting an optimal solution) and the quality index for the selected design point or selected car (the quality index calculation is described in the next section). Also, we noted the number of actions performed to finally choose a car and the time spent between actions in order to identify the influence of the graph on the path. "Action" refers to all interactions with the graphic tool.

[1] http://camstudio.org/

It uses the "brush", "filter" or "sorting" function. Every action is an indication of the designer's mental activity (data mining). These four variables are collected during the scenario phase.
We used a questionnaire at the end of the experiment to obtain "subjective" measurements: Influence of the graph on the cognitive load and Influence of the graph on the level of confidence. To measure cognitive load we chose the DALI method (Pauzié, 2008) which is the method which provides the greatest breakdown of the cognitive load through its questionnaire compared to NASA TLX or SWAT (visual effort, for example). We also adapted DALI to our case (DALI is designed for driving so we adapted the questions for the design selection). Answers to questions are given on a scale of 0 to 100. Finally to determine the influence of the graph on the level of confidence, we used the Aloysius et al. (2006) method adapted to our case. For this, we have two variables: Level of certainty in the chosen solution and the preference for one graph. As for the cognitive load, answers are given on a scale of 0 to 100. The set of measures is summarized in Figure 4.

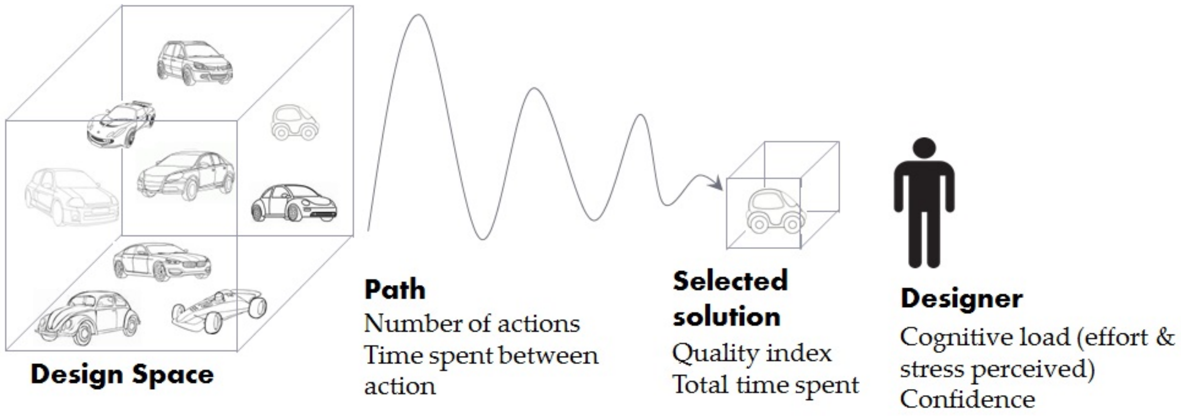

Figure 4. The experiment's measurements

4.2 Quality index

As already mentioned, in all three scenarios, the subject was asked to explore possible solutions (design points) and select the ideal car according to the scenario. To do this, five performance variables have to be either maximized or minimized. For each scenario, a quality index i_j is calculated (Equation 1) and then a global quality index i is calculated (Equation2).

$$i_j = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{f_k(P)-f_k(A)}{f_k(I)-f_k(A)}\right| \tag{1}$$

$$i = \left|\frac{i_j - i_{j_{\min}}}{i_{j_{\max}} - i_{j_{\min}}}\right| \tag{2}$$

Where f_k is a performance variable and $k = \{1;...;n\}$ (n=5 for each scenarios). $f_k(P)$ is the value of design point *P* for the variable f_k. And:

- If f_k is maximized: $f_k(A)$ = the minimum value of f_k and $f_k(I)$ = the maximum value.
- If f_k is minimized: $f_k(A)$ = the maximum value of f_k and $f_k(I)$ = the minimum value.

(*I* for the Ideal and *A* for the Anti-Ideal). We then calculate the global basic index i with equation (2) so as to get a value below or equal to 1, 1 being the best car considering the 5 variables of performance with an identical weighing. With this method, the selections of the ideal car in the three cases are comparable.

5 RESULTS

5.1 Influence of the Graph on the selected solution

We have a sample of N = 30 subjects and it is a within approach (3 groups). Also, all measured variables during the test are quantitative. Therefore we apply the ANOVA-within statistical test.
The results for trade-offs are not significant. We obtain $F(2,58)=0.283$ and $p=0.75$ for the quality index and $F(2,58)=1.12$ and $p=0.33$ for the response time. There are therefore no significant differences between the three graphs for the selected solution.
Indeed, we observe good results (i.e. high index of quality) for the three graphs: $i=0.89$ with PCP, $i=0.86$ with RC and $i=0.89$ with CT.

5.2 Influence of the graphs on the path (data mining)

As in the previous section, we have a sample of N = 30 subjects and it is a within approach (3 groups). Also, all measured variables during the test are quantitative. Therefore we apply ANOVA within statistical test (and the T-test for the post-hoc analysis).
The results for the performance of data mining are significant because we obtain $F(2,58)=14.1$ and $p=0.0001$ for the number of actions carried out and $F(2,58)=10.7$ and $p=0.0001$ for the average time between actions. So we perform a post-hoc analysis: t-test pairwise comparison (see Table 1).

Table 1. Results for the t-test for the action number and for the time between actions

T-test pairwise comparison	for the number of actions	for the time between actions
[PCP] vs [RC]	$t(29)=3.81$ $p< 0.0007$	$t(29)=3.90$ $p< 0.0005$
[PCP] vs [CT]	$t(29)=4.22$ $p< 0.0002$	$t(29)=5.02$ $p< 0.0001$
[RC] vs [CT]	$t(29)=0.46$ $p< 0.6496$	$t(29)=1.92$ $p< 0.0652$

The results of these tests show that the PCP is the most efficient for data mining with an action number equal to 9.67 and an average time between actions 26.2 seconds compared to 3.97 action numbers for RC and 3.60 for CT and 73.0 seconds between actions for RC and 50.3 seconds for CT.

5.3 Graph's influence on the designer

For the analysis of "preference" measurements, we use ANOVA within (and t-test) for statistical analysis (N = 30) and we consider a significance level $\alpha=10\%$.

5.3.1 Cognitive load

The cognitive measurement is divided into three indicators: the effort of attention and visual and the stress perceived. The results for the three indicators are significant. We obtain $F(2,58)=2.77$ and $p=0.07$ for the effort of attention, $F(2,58)=3.40$ and $p=0.04$ for the visual effort and $F(2,58)=7.24$ and $p=0.001$ for the perceived stress. So we perform a post-hoc analysis: t-test pairwise comparison (see Table 2).

Table 2. Results of the T-tests for the three indicators of the cognitive load

T-test pairwise comparison	for the effort of attention	for the visual effort	for the perceived stress
[PCP] vs [RC]	$t(29)=1.93$ $p< 0.0628$	$t(29)=2.52$ $p< 0.0173$	$t(29)=2.65$ $p< 0.0128$
[PCP] vs [CT]	$t(29)=0.44$ $p< 0.6636$	$t(29)=0.22$ $p< 0.8307$	$t(29)=1.27$ $p< 0.2126$
[RC] vs [CT]	$t(29)=2.03$ $p< 0.0512$	$t(29)=2.15$ $p< 0.0400$	$t(29)=3.47$ $p< 0.0017$

The results of these tests show a significant difference for RC with the most effort with 63.28/100 attention (compared to 51.44 for PCP and 48.61 for CT), visual effort of 67.67/100 (compared to 54.39 for PCP and 53.00 for CT) and a perceived stress of 64.12/100 (compared to 48.83 for PCP and 41.13 for CT). We cannot conclude any difference between PCP and CT.

5.3.2 Confidence

The confidence measurement consists of two indicators: the level of certainty and preference (for data mining and to select one solution).

The results for the level of certainty are not significant. We obtain F(2,58)=2.30 and p=0.11. We therefore cannot conclude that there is a significant difference between the three graphs for this indicator (PCP=55.61/100; RC=50.44/100 and CT=63.83/100).

Finally, the graph preference for the design process' selection phase is tested with two modalities: the preference of one graph for data mining and selecting one solution. In this part we use the Friedman test for statistical analysis because the answers are ranks and we have 3 within groups.
Then the results for the preference are significant. We obtain csqr=16.47, df=2 and p=0.0003 for data mining and csqr=9.8, df=2 and p=0.0074 for decision-making. There is a difference between the three graphs for these two modalities. So we perform a post-hoc analysis: Wilcoxon signed-rank test pairwise comparison (N=30>20 so we consider the W-value) (Table3). For N=30 at p>0.05, W-value=137.

Table 3. Results of the T-tests for the three indicators of confidence

Wilcoxon signed-rank test pairwise comparison	for data mining	to select one solution
[PCP] vs [RC]	W-value=65 (p<0.05)	W-value=91 (p<0.05)
[PCP] vs [CT]	W-value=206	W-value=189
[RC] vs [CT]	W-value=85 (p<0.05)	W-value=132 (p<0.05)

The results of these tests show a significant difference for RC which is the least preferred graph with a rank=2.6 for data mining (compared to 1.6 for PCP and 1.8 for CT) and rank=2.4 to select one solution (compared to 1.6 for PCP and 1.9 for CT).

5.4 Synthesis results

To sum up our results, we have a greater performance for the "path" (ie. data mining) with the graph Parallel Coordinates Plot (PCP). There is no distinction between the three graphs for the selected solution (both quality index and time indicators). Furthermore, the designer is less satisfied than with the graph Radar Chart (RC). The results are summarized in Table 4.
We should therefore conclude that the Parallel Coordinates Plot (PCP) is the best graphic support to help designers select one optimal solution whilst exploring the design space.

Table 4. Synthesis of our results

	The path	The selected solution	Designer felt
Best graphs	PCP	none	PCP ≡ CT
Worst graphs	CT ≡ RC		RC

6 CONCLUSION AND DISCUSSION

In conclusion, our experiment delivers clear recommendations regarding the choice of a graph for the selection phase in Design by Shopping to efficiently select an optimal solution in a set of feasible solutions defined by their design and performance value vectors.
Indeed, our results show that it is more efficient to use the Parallel Coordinate Plot that meets higher performance. Note that our recommendations apply design multicriteria decision or in other words the realization of trade-offs between conflicting objectives to obtain an optimal solution. In fine, we could propose the use of two graphs on the same screen. The Parallel Coordinate Plot is particularly useful for data mining and the selection of an alternative whereas the combined table is specifically to support disseminating information in detail (e.g. a specific value). Nevertheless, it is necessary that the two graphs match (linked views) i.e. if a filter is applied to one, the data must be filtered on the other automatically.
The development of our work aims at addressing a graphical solution for designers in the context of the preliminary design with selection by reducing the space of possible (i.e. design space).

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