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# DATA VISUALIZATION IN CONCEPTUAL DESIGN: DEVELOPING A PROTOTYPE TO SUPPORT DECISION MAKING

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## ABSTRACT:

*In recent years, data visualization has received a lot of attention and widely applicate in many areas. Data is a treasure, a lot of valuable information hidden inside. While visualizing the hidden information concisely and intuitively is a critical task. In this paper, we explore how data visualization could support conceptual design. A specific conceptual design case for improving the fuel efficiency of wheel loader is implemented. By visualizing the complex fuel consumption data comprehensive for engineers to get insights, thus to support the decision making for a new product development. As a result, a table of classifying visual techniques by different features, and a prototype consisted of four approaches step by step to present complex data are proposed.*

**KEYWORDS:** *complex data visualization, conceptual design, prototype, decision making*

## 1 INTRODUCTION

During the process of conceptual design, that takes place in the early stages of a system development project, several (often critical) decisions need to be made. A successful product is often the result of a combination of right decisions taken by engineers and managers (Bertoni et al., 2017). Uncertainties in decision-making associated with the need to shorten design cycle require increased skills and tools to support complex decision making (Platt and Huettel, 2008; Eriksson et al., 2008).

With the advent of digital technologies, important amounts of data are available, enabling engineers and project managers to access these data, explore patterns, proceed to several diagnoses and prognostics, and to collect insights for decision-making. However, effectively extracting and summarizing information so to avoid information overload and to enable its interpretation is a challenge (Keim et al., 2006). For this goal, numbers of visualization techniques have been developed to display massive data information.

The main object of this article is exploring suitable tools to visualize complex data information in a readable way in order to help engineers understand a current situation from a large collection of data before a new concept design. The paper considers a case study from product development to illustrate the method. Section 2 reviews the relative literature on conceptual design, data visualization, and the possibility as well as the challenge of applying data visualization to support conceptual design. Section 3 presents the case study and the process of design a visualization within the case, which starts with benchmarking visual techniques, followed by applying suitable tools into the case, then testing those techniques and analyzing the testing result. Section 4 presents a fi-

nal prototype. Section 5 discusses the contributions of the proposed prototype and limitations of the experiments. Section 6 draws come conclusions.

## 2 LITERATURE REVIEW

This chapter illustrates conceptual design, data visualization, and how data visualization can support conceptual design.

### 2.1 Conceptual design

Conceptual design is the first stage in the product development process. It identifies a basic solution path by the elaboration of a solution principle (Stump et al., 2004). The target of conceptual design is to study possible ideas, and after evaluation to select the best one(s) to satisfy the project goal (Stump et al., 2004).

In this stage, the comprehension of the users' needs and associated constraints is a critical activity. To support it, many computer-based tools are being developed and applied, for simulations, analyses, optimization, and visualization (Wang et al., 2002). The implementation of data visualization in concept development is a striking trend (Hasem et al., 2015).

### 2.2 Data visualization

(Card et al., 1999) explain data visualization as “*using computer-supported, interactive, visual representation of data to amplify cognition, where the main goal of insight is discovery, decision-making, and explanation.*” Thanks to the visualization technologies to raise availability of the abundant data, as well as the approaches to process it, data visualization will become the ‘next mass communication medium’ (Viegas and Wattenberg, 2011).

Although data visualization has existed for a long period of time, its need of serving for different purposes is growing rapidly (Donoho et al., 2000). A primary goal for data visualization is transferring information clearly and efficiently by different kinds of graphs and maps. In this research, we focus on engineering environments and explore suitable visualization tools to help engineers' visual the complex data. A variety of visualization tools are available for presenting data information; section 3.2 will later present a benchmarking table on commonly used visual tools.

### 2.3 Data visualization to support conceptual design

Decisions made during the conceptual design stage have a profound influence on a final product on the cost, performance, reliability, safety and environmental impact (Hsu and Liu, 2000). In addition, it has been proven that it is more challenging and costly to correct or compensate shortcomings of poor design concepts in later design stages (Hsu and Liu, 2000). It is therefore critical to support the conceptual design phase with advanced techniques so to best guide engineers.

With the advent of data collection and visualization techniques, many opportunities are available to allow flexible access to data source for value creation (Hasem et al., 2015). A clear structure of data visualization assists in knowledge production, insight gathering, relation discovery and understanding the information and underlying patterns. As such it is impacting conceptual design and decision-making (Shim et al., 2002).

(Kellen, 2005) discusses how imagery helps in making decisions. (Benn et al., 1994) indicates that imagery shows two important problem-solving and decision-making activities: distinguishing a problem from the symptoms, and deciding upon and implementing a course of action. The initial purpose of visualization is to make graphs and to support for structured thought processes (Few, 2009). Data visualization, on the one hand, gives the potential that enables people to become more engaged to select the presented information; on the other hand, it leads users to make discoveries and decisions.

### 2.4 The challenge of data visualization to support conceptual design

Relatively few work has been done on data visualization for the early of product design in an engineering environment (Graham et al., 2000). While data visualization tools used in these early stages has not proven to be as useful as in the final stage of product development (Anderson et al., 2004), (Mc Gown et al., 1998) concluded that many researchers have chosen to turn their attention to developing support techniques for later design stages. (Knopp, 1995) mentions that the technology push, coupled with a poor understanding of the design process, has led to the current lack of support for the conceptual designers. In this research, we explore how to visualize complex data for easy insights gathering by a concise

and easy readable way, thus to further support decision making in conceptual stage.

## 3 DATA VISUALIZATION DESIGN

This research follows the design research methodology proposed by (Blessing and Chackrabarti, 2009). Following this methodology, one case about wheel loader fuel consumption is applied; original data are gathered for visualizing. Following the benchmarking guidelines of (Camp, 1989), a range of visualization techniques are assembled and classified by distinguishing visual features. Subsequently, based on the needs of engineers, suitable tools are selected for first round visualization. After valuable feedbacks and suggestions are received from an experiment, empirical findings are contributing to the final visual prototype design.

### 3.1 Case background

Pushed by environmental protection and energy saving, construction industry desires to develop more efficient and energy-saving machines to reduce the effect on environment (Yeam et al., 2007). Improving current machine efficiency and developing new low energy consumption products are two effective solutions (Cronholm, 2013). Both solutions require a good understanding of the operation conditions of current machines (Bertino, et al., 2017); a set of operating data was collected from existing machines.

#### *Data types in the case*

The different data types guide to the different scope of selecting visualization tools in a case. In this case, 234 fuel consumptions items, from wheel loader working in different situations, are collected.

#### *The needs*

To help engineers understand the current machine' performance, some specific information is needed (Bertoni, 2017):

1. What is the general fuel consumption when operating in the different situation?
2. What is reason leading to different fuel consumption?
3. Which parameter player a greater impact on fuel consumption?

#### *Envision data relationship*

Data relations need to be revealed based on engineers' needs:

1. Showing the overall fuel consumption in one situation, which specifies tools with functions of displaying massive data and showing the relation of part to whole.
2. Displaying the different levels of fuel consumptions for pattern explore is indicating the relation of deviation.
3. Presenting the impact of one variable on the whole fuel performance.

#### *What features of visualization tools are required?*

Based on the needs and data type, the main features of visualization methods in this case are comparison, distribution, deviation, part to whole.

### 3.2 Benchmarking of visualization techniques

Although many novel data visualization techniques have been developed (Card et al., 1999), no visualization method is suitable to address all the problems (Grinstein, et al., 2002). A benchmarking on visualization methods was done (see Table 1 for the tools studied).

Visualization feature	Visualization techniques
Comparison	Bar chart
	Box-plot chart
	Butterfly chart
	Scatter plot
	Stacked bar chart
	Table
Distribution	Line chart
	Bubble chart
	Box plot
	Parallel sets
	Circle view
	Scatter plot
Deviation	Box-plot chart
	Parallel sets
	Circle view
	Scatter plot
	Butterfly chart
	Waterfall chart
Part to the whole	Pie chart
	Parallel sets
	Stacked bar chart
	Treemap
	Bar chart

Table 1: Benchmarking result

### 3.3 Visualization techniques application

In order to allow information “hidden” in the data to become more comprehensive for engineers, the visualization is divided into three main scenes based on engineer’s needs: showing the overall fuel consumption, displaying the special cases, and comparing parameter impact on total value. The first scene aims to allow engineers obtaining an overall view of fuel consumption when wheel loader operating in different situations. Followed that, the second scene helps engineers get insights of the reason (which variables) that distinguishing the levels of fuel consumption. Then the third scenes move further to compare the impact of parameters on whole fuel performance.

#### Scene 1: Showing the overall fuel consumption.

In this condition, fuel consumption cases under the same operation are exhibited. Since the fuel performance varies a lot in the different operating scene, the different working scenes are designed separately. This allows for simplifying the visualization and for easier version assembling. Table 2 shows eight types of visual techniques used to exhibit the overall fuel consumption.

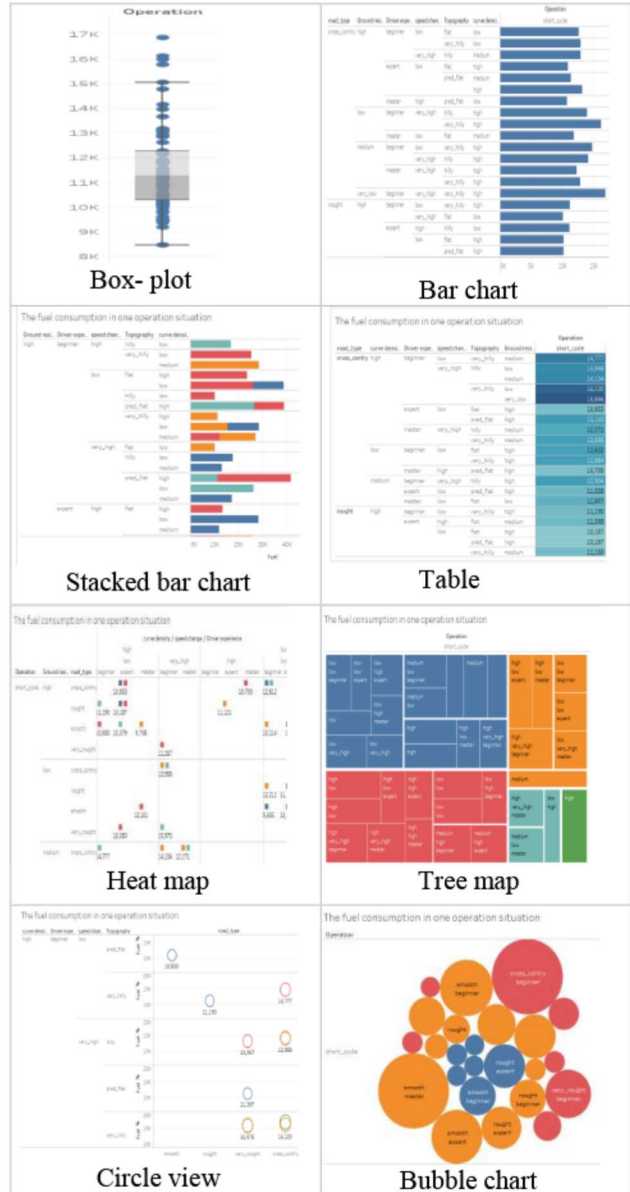


Table 2: All the visualization applied in scene 1

#### Scene 2: Displaying the special cases

The second visual scene is designed for indicating the special fuel performance occasions to bring convenience for engineers to figure out the reasons for fuel consumption variation. There are four tools are implemented, which are bar chart, butterfly chart, box-plot and scatter plot are presented in table 3.



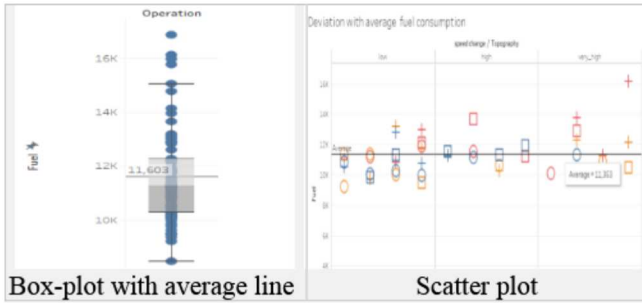


Table 3: All the visualizations applied in scene 2

**Scene 3: Comparing parameter impact on total value**  
 The final visual situation concentrates on comparing the parameters impact on the total fuel performance. There are two modes of techniques utilized. Table 4 displays the result.



Table 4: All the visualization applied in scene 3

### 3.4 Experiment set-up

To test the intuitiveness of the chosen tools, an experiment was designed, and empirical data collected. The experiment involved four engineers and lasted one hour. It was started with 15 minutes introduction of task background and the visualization tools, followed by a 30 minutes session where engineers were asked to find patterns and get insights within the provided visualization techniques. After that, an additional 15 minutes session, where engineers communicated findings, sharing the suggestions for improving, and filled a questionnaire separately to score the tested tools.

### 3.4 Data analysis

Various techniques are applied in three visualization scenes, hence, the analysis is conducted separately under each situation to figure out which tool is more intuitive for engineers.

Table 5, 6 and 7 summarise the results on tool suitability from engineers’ perspective in each visualization scene. The technique that applied in per scene are listed in the left column, and the engineers’ labels are put in the first row. To the question “Do you think this method is clear to show the overall fuel performance?” engineers had to score all tools from zero to two (0=unintuitive, 2=intuitive). A final score for each tool is obtained by summing up the single scores.

Visual tools	EngA	EngB	EngC	EngD	Total Score
Circle view	1	0	0	0	1

Heat map	0	0	0	0	0
Table	2	1	1	0	4
Tree map	1	0	2	0	3
Staked bar chart	1	0	1	0	2
Bar chart	2	1	1	1	5
Box-plot	2	1	1	1	5
Packed bubble	0	0	1	1	2

Table 5: Analysis result in visual scene 1

In the scene 1, bar charts and box-plots were considered as the most readable tools to show the overview fuel consumption. Tables were also judged suitable. However, circle views and heat maps are clearly not applicable in this visual context.

Visual tools	EngA	EngB	EngC	EngD	Total Score
Bar chart	2	1	1	2	6
Butterfly chart	2	2	2	2	8
Box-plot	0	0	2	1	3
Scatter plot	1	2	1	1	5

Table 6: Analysis result in visual scene 2

From the analysis result, in the scene 2, all engineers agreed that butterfly charts are best suited to show the deviation. Bar charts also obtained a high score, while box-plots appear inappropriate in this visualization.

Visual tools	EngA	EngB	EngC	EngD	Total Score
Bar chart	2	0	2	0	4
Bubble chart	1	0	1	0	2

Table 7: Analysis result in visual scene 3

In the scene 3 that compares the impact of parameter to the whole fuel consumption, only two prototypes are made: a bar chart and a bubble chart. The bar chart gained more support than bubble charts in this scene.

## 4 PROTOTYPE

A number of visualization techniques have been applied to seek feedbacks from engineers of weighing the intuitiveness for insight gathering. Based on comments and suggestions, a final prototype consisted of several visualization techniques is put forward to deal with complex data visualization case of improved fuel efficiency from wheel loader. The visualization is divided into three scenes, including know the overall fuel consumption, patterns visualization in different clusters, and comparing the impact of parameters on total value. To corresponding each scene, four visual approaches are proposed, due to two different techniques are applied in scene two.

The logic of the designed prototype is to first present the overall fuel consumption, followed by pattern visualization in cluster. Furthermore, revealing the impact of a single variable change on the overall fuel consumption. Box-plots are used to show the overall fuel performance in one operation. See below Figure 1. This approach displays a large number of data in a concise and easy

understanding way, which had been proved on experiment. Clusters are marked with colours to divide fuel performance into five groups: low, middle, upper middle, high, and extreme. In each cluster, the number of items and average fuel level are displayed in Table 8.

**Stage 1: know the overall fuel consumption**

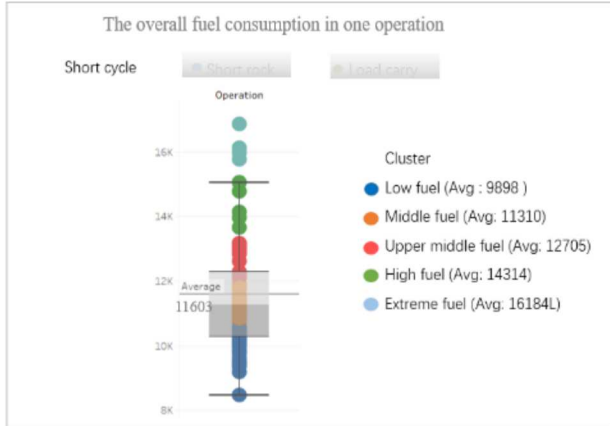


Figure 1: Approach 1 of showing the overall situation

In this visualization case, there are 22 numbers of items in cluster 1 and the average fuel consumption is 9898. Similarly, 26 numbers of elements in cluster 2 and with an average fuel consumption of 11310. Besides, there are 12, 5, 4 number of items with the average fuel consumption of 12705, 14314 and 16814 respectively in cluster 3, 4, and 5. Table 8 shows the cluster classification.

Cluster (different fuel consumption)	Number of items	Average fuel consumption
1: Low	22	9898
2: Middle	26	11301
3: Upper middle	12	12705
4: High	5	14314
5: Extreme	4	16184

Table 8: cluster classification

When clusters of fuel consumption are obtained, other questions should be addressed for further insights gathering. What is reason leading to the diverse levels of fuel consumption? What is the commonality feature of parameters in each cluster? To find answers for these questions, other visualization methods are implemented. The questions will be answered by the following visualization.

**Stage 2: Patterns visualization within different cluster**

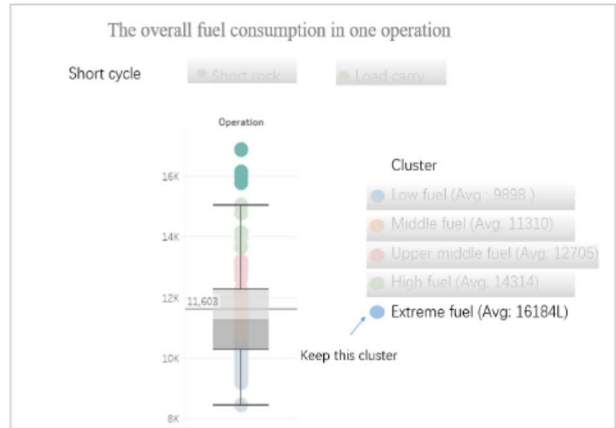


Figure 2: A cluster selection - Small amount of data sets for pattern visualization

The cluster marked in light blue (see from Figure 2), indicating the highest level of fuel performance is selected for insight observing. In this cluster, four items need to be explored further for patterns. A bar chart is used for data visualization since it with comparison function, simple for vision collection and engineers are familiar with this data visualization. Bar charts are selected to organize and visualize the deep information in the highest fuel consumption cases and identify what characteristic parameters are leading to such high fuel consumption. GIF-format information (graphic interchange format) next to each variable allows for describing different meanings of parameters. GIF combined with bar chart was retained as a solution to make visualization intelligible for engineers.

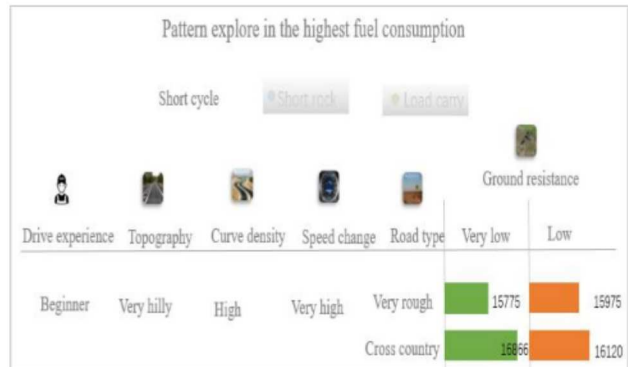


Figure 3: Approach two- Pattern explore in cluster with small number data sets

From this visualization (Figure 3), it is easy to conclude the similarity of parameters which contribute the high fuel consumption. In this case, a combination of extreme road types (very rough and cross-country) combined very hilly terrain, high curve density and very high-speed changes explained the high fuel consumption.

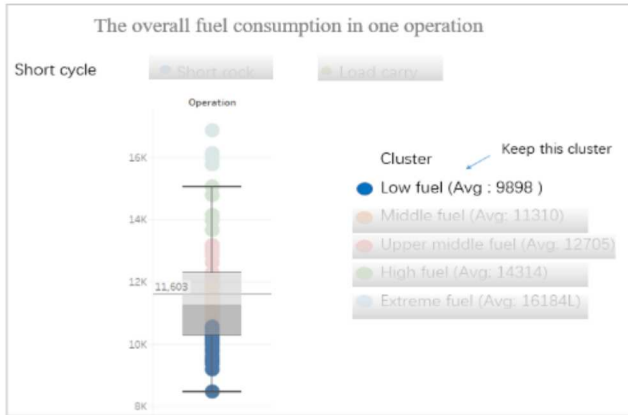


Figure 4: A cluster selection – Large amount of data sets for pattern visualization

Figure 4 displays the cluster 1, with 22 numbers of data sets, is chosen to explore commonality resulting in the lowest fuel consumption. The 22 numbers of data sets with 6 variables are not organized in the same way as in the previous visualization situation of cluster 5 that only had quintuple data sets. Consolidated the results of interviews and questionnaires, scatter plot with an added horizontal line has a higher advantage over the butterfly chart in an area of patterns exploring and parameters tracking particularly under the situation of many items and parameters. Therefore, a scatter plot substitutes the bar chart and butterfly chart to visualize patterns in a cluster with more data sets.

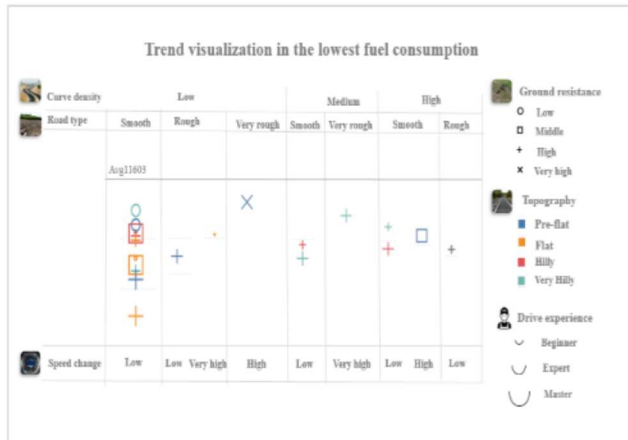


Figure 5: Approach three - Pattern explore in a cluster with more data sets

Scatter plots are applied for patterns visualization as well as with the feature of showing the fuel consumption deviation with the baseline under the situation of many data sets in one cluster. To make the visualization concise and intuitive for pattern explore, three variables (topography, ground resistance, and driver experience) are signed with different colors, symbols, and sizes in the visualization. As before, a GIF nearby each category relates to the corresponding situation of the parameter in the variables.

Many insights can be obtained from this prototype. In the visualization above, taking the pattern tracking by the size of the symbol for example, it is not hard to find

out that the symbol with big and middle sizes are account for the majority and only 3 symbols in small. It is here demonstrated that in most scenes of low fuel consumption, the machine is operated by a master and expert, as the middle size and big size are corresponding to expert and master respectively. Meanwhile, the three individual cases in small size symbols could be selected out to analyze further and figure out in which conditions that beginner also could lead to low fuel consumption. Furthermore, this visualization shows fuel consumption under the average performance – around halve of the cases are gathered in the left half of the page, indicating low curve density situations with smooth road type and low speed changes.

The scatter plot provides approaches of patterns and commonality exploration in clusters. When necessary engineers can conclude of out some parameters leading to high or low fuel consumption which variables or parameters are of highest impact. The here presented visualization method allows for showing the effect of a variable on the overall fuel consumption. Bar charts provide a good method for comparative visualization. In this prototype, the highest fuel performance cases were selected to explore which parameters and variables had the highest impact on fuel consumption.

**Stage 3: comparing variable’ impact on total value**

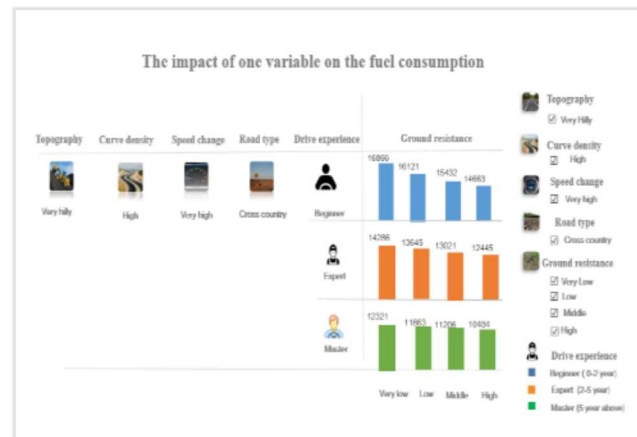


Figure 6: Approach Four - Comparing the impact of one variable to total value

In the visualization process, four variables have remained unchanged; driver experience and ground resistance are selected to make a comparison. In the right part of the dashboard, a filter is used for changing to different variables that engineers interested, and the corresponding data information would be presented in the left part of the dashboard. In this visualization, it is not hard to identify that with the ground resistance parameter changing from very low to high, the fuel consumption varies.

In comparison, fuel consumption varies more when altering drive experience from beginner to master under the same ground resistance circumstance. Therefore, it can be concluded the variable driver experience has a higher impact on total fuel consumption than ground resistance. In addition, the other insight is that fuel

consumption varies more when beginners and experts operate the machine.

## 5 DISCUSSION

In this section, the limitation of testing, the interesting findings from the experiment and the wider applicable scenarios of final prototype would be discussed below.

### 5.1 Test discussion

(Nielsen and Landauer, 1993) suggest that the best results in such research come from tests with no more than five participants and involving as many as small tests as possible. Bartlett et al. (2001) on the other hand suggest sample selection in one test to increase the reliability of data. Data visualization in design processes is a non-linear and iterative activity, which means that more tests are needed to collect feedbacks for continuing prototype improvement. So, even though in this study only four engineers were available, the by (Nielsen and Landauer, 1993) proposed approach was followed and feedback and suggestions for improvement of the tool, an experiment was carried out involving those four engineers.

### 5.2 Results discussion

Four different visualization approaches were investigated in series so to visualize complex data in the case of the fuel consumption improvement of a wheel loader. Even though the realized prototype is based on a special case, it is not limited only to this particular case situation. The following applicable scenarios can be seen for the prototype.

#### *Approach one – show the overall fuel consumption*

Box-plots were implemented here to show the cases of fuel performance. This approach shows to be useful only in a situation of presenting massive data from a bird view without requirements for detailed information. Color-marked clusters could be introduced to differentiate data sets so to bring convenience for further analysis (Fraley et al., 2002).

#### *Approach two – pattern visualization in a cluster with less data sets*

Similar levels of fuel consumption are assembled in one cluster to differentiate from others. Deep exploration takes place as to the reasons leading to the distinguished levels of fuel consumption in a small number of data sets. Bar charts allow for efficient data visualization of such analyses.

#### *Approach three – pattern visualization in a cluster with more data sets*

For more complex datasets, scatter plots express data in a horizontal direction bringing convenience for trend tracking. Various color, symbol and size are used to identify different variables for clear and easy pattern investigating. Scatter plots, combining the function of the commonality exploring and trend tracking, offer a

good tool for insights gathering.

#### *Approach four – comparing the impact of variable on the whole value*

Bar charts with an interactive interface allowing engineers to change parameters so to compare the impact of variable on the overall fuel consumption. GIF-pictures can offer an intuitive manner to represent different parameters in a comprehensive manner for engineers.

### 5.3 Discussion of the test results in relation with literature

Box-plots are considered as a useful tool to show a large number of data and highlight data distribution (Potter et al., 2006). This technique was applied and tested in two visualization situations of showing overall fuel consumption and showing the deviation with baseline. In this experiment, box-plots gained the highest scores for displaying the situation of overall fuel consumption. Low scores were obtained for showing the deviation. These results do not confirm results presented by (Potter et al., 2006) that box plots are a valuable tool to depict data as well as to spotlight data distribution. From the test, a box plot was seen not to be effective to get insights from the deviation perspective.

Scatter plots with added reference lines of average fuel consumption reached a consensus from interview results for showing deviations. They offer an interesting for box-plots and should be further investigated (see also (Kampstra, 2008)). The test also shows that scatter plots are more intuitive and easy for the pattern and trend tracking. Scatter plots with added reference lines could be taken into consideration to replace box-plots in visualization conditions in which there is the need to show deviation as well as patterns tracking of parameters

## 6 CONCLUSION

The aim of the research was carried out to explore how to visualize complex data comprehensively for easy insights gathering thus to support decision making in conceptual design. To reach this goal, the paper is presenting a prototype consisted of four approaches to visualize multidimensional data concisely and readably, showing “hidden” information and patterns, with as intend to support decision-making in the conceptual design phase. The research focused on complex data (multi-dimensional data) visualization and specifies an application to visualize the data of the fuel consumption of a wheel loader. The approaches in the final prototype, a single or in series, also work for other conceptual design cases when dealing with complex data visualization. The final prototype has been iteratively developed based on results of the analysis runs with engineers.

## 7 REFERENCES

- Anderson, E., & Lily, B. (2004). Visualization in the Design Process: Introducing two and three-dimensional sketching techniques to enhance creative thinking and communication. In *International Engineering and Product Design Education Conference* (pp. 2-3).
- Bartlett, J.E., Kotrlík, J.W. and Higgins, C.C., 2001. Organizational research: Determining appropriate sample size in survey research. *Information technology, learning, and performance journal*, 19(1), p.43.
- Benn, D.I., 1994. Fluted moraine formation and till genesis below a temperate valley glacier: Slettmarkbreen, Jotunheimen, southern Norway. *Sedimentology*, 41(2), pp.279-292.
- Bertoni, A.; Larsson, T.; Larsson, J.; Elfberg, J. Mining (2017). Data to design value: a demonstrator in early design. Accepted for publication in *Proceeding of the 21st International Conference on Engineering Design (ICED17)*, Vancouver, Canada.
- Blessing, L.T., Chakrabarti, A. (2009). "DRM: A Design Research Methodology", Springer London.
- Camp, R.C. (1989). Benchmarking: the search for industry best practices that lead to superior performance. In *Benchmarking: the search for industry best practices that lead to superior performance*. ASQC/Quality Resources.
- Card, S. K., Mackinlay, J. D., & Shneiderman, B. (Eds.). (1999). *Readings in information visualization: using vision to think*. Morgan Kaufmann.
- Cronholm, K., (2013). Design of Experiment based on VMEA (Variation Mode and Effect Analysis). *Procedia Engineering*, 66, pp.369-382.
- Donoho, D.L. (2000). High-dimensional data analysis: The curses and blessings of dimensionality. *AMS Math Challenges Lecture*, 1, p.32.
- Eriksson, J., Johnsson, S. and Olsson, R., (2008). Modelling decision-making in complex product development. In *DS 48: Proceedings DESIGN 2008, the 10th International Design Conference, Dubrovnik, Croatia*.
- Few, S., (2009). Now you see it. *Simple Visualization Techniques for Quantitative Analysis*, Analytics Press, Oakland, CA, pp.33-35.
- Fraley, C., & Raftery, A. E. (2002), "Model-based clustering, discriminant analysis, and density estimation," *Journal of the American Statistical Association*, 97, 611-631
- Graham, M., Kennedy, J. and Benyon, D., (2000). Towards a methodology for developing visualizations. *International Journal of Human-Computer Studies*, 53(5), pp.789-807.
- Grinstein, G. G., Hoffman, P., Pickett, R. M., & Laskowski, S. J. (2002). Benchmark development for the evaluation of visualization for data mining. *Information visualization in data mining and knowledge discovery*, 129-176.
- Hashem, I.A.T., Yaqoob, I., Anuar, N.B., Mokhtar, S., Gani, A. and Khan, S.U. (2015). The rise of "big data" on cloud computing: Review and open research issues. *Information Systems*, 47, pp.98-115.
- Hsu, W. and Liu, B., (2000). Conceptual design: issues and challenges. *Computer-Aided Design*, 32(14), pp.849-850.
- Platt, M.L. and Huettel, S.A., (2008). Risky business: the neuroeconomics of decision making under uncertainty. *Nature neuroscience*, 11(4), p.398.
- Kampstra, P. (2008). Beanplot: A boxplot alternative for visual comparison of distributions.
- Keim, D.A., Mansmann, F., Schneidewind, J. and Ziegler, H. (2006). Challenges in visual data analysis. In *Information Visualization, 2006. IV 2006. Tenth International Conference on* (pp. 9-16). IEEE.
- Kellen, V. (2005). Decision making and information visualization: research directions. Retrieved November, 11, p.2005.
- Knopp, R. and Humblet, P.A. (1995). Information capacity and power control in single-cell multiuser communications. In *Communications, 1995. ICC'95 Seattle, 'Gateway to Globalization', 1995 IEEE International Conference on* (Vol. 1, pp. 331-335). IEEE.
- Nielsen, J., & Landauer, T. K. (1993). A mathematical model of the finding of usability problems. In *Proceedings of the INTERACT'93 and CHI'93 conference on Human factors in computing systems* (pp. 206-213). ACM.
- Potter, K., Hagen, H., Kerren, A., & Dannemann, P. (2006). Methods for presenting statistical information: The box plot. *Visualization of large and unstructured data sets*, 4, 97-106.
- Shneiderman, B. (2003). The eyes have it: A task by data type taxonomy for information visualizations. In *The Craft of Information Visualization* (pp. 364-371).
- Shim, J.P., Warkentin, M., Courtney, J.F., Power, D.J., Sharda, R. and Carlsson, C. (2002). Past, present, and future of decision support technology. *Decision support systems*, 33(2), pp.111-126.
- Stump, G. M., Yukish, M., Simpson, T. W., & O'Hara, J. J. (2004). Trade space exploration of satellite datasets using a design by shopping paradigm. In *Aerospace Conference, 2004. Proceedings. 2004 IEEE* (Vol. 6, pp. 3885-3895). IEEE.
- Viegas, F., & Wattenberg, M. (2011). How to make data look sexy. *CNN.com*, April, 19.
- Wang, L., Shen, W., Xie, H., Neelamkavil, J. and Pardasani, A., (2002). Collaborative conceptual design—state of the art and future trends. *Computer-Aided Design*, 34(13), pp.981-996.
- Yeam I, Cavatorta JR, Ripoll DR, Kang BC, Jahn MM (2007) Functional dissection of naturally occurring amino acid substitutions in eIF4E that confers recessive potyvirus resistance in plants. *Plant Cell* 19: 2913-2928.