공학석사 학위논문

A Comparative Evaluation of Design Structure Matrix (DSM) and Node-link Diagram Focused on Engineering Design Use

공학적 설계를 위한 **Design Structure Matrix**와 **Node-link diagram**의 비교 평가

2015년 12월

서울대학교 대학원

산업공학과

김 동 우

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이 논문을 산업공학 석사 학위논문으로 제출함

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Abstract

A Comparative Evaluation of Design Structure Matrix (DSM) and Node-link Diagram Focused on Engineering Design Use

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The objective of this research is to evaluate typical visualization techniques for given engineering design and changes. Specifically, this study attempts (1) to determine the comparative attributes of visualization techniques for engineering design, and (2) to scrutinize the difference and efficiency between different visualization techniques based on defined attributes. A visualization technique in engineering design can be described as a user interface between engineering information and an engineer. Engineers can be affected by the way information is presented during engineering design tasks. A user test was conducted to discover which visualization technique is better in certain engineering design contexts. During the research, we found that there is a difference between two visualizations in terms of some aspects. It is expected that our research procedure can be applied to compare or evaluate visualization techniques for engineering design. It also has raised many questions in need of further research, such as aesthetics, data usability, and domain knowledge.

Keywords: Information Visualization, Comparative Evaluation, Engineering Design, Engineering Change, Data Envelopment Analysis

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1. Introduction

Many products have been launched with changes to be competitive in their respective markets. Typically, they try to be more attractive by releasing their updated outputs rather than making perfect new ones (Cross, 2008). The purposes of engineering change management involve tracing footprints of change, predicting and preventing its ripple effects. It is significant for engineers and designers who manage change propagation to develop strategic decisions for product development and maintenance. Understanding product architecture and engineering change propagation is one of the overarching tasks for engineers. A visualization technique in engineering design is a user interface between engineering information and an engineer. In terms of interfaces for information, users interact with it and are affected by the way information is represented (Luzzardi, Cava, Winckler, Pimenta, & Nedel, 2002). However, there have been few controlled research studies that investigate methods to present engineering design.

There are various visualization techniques for engineering design, such as matrix-based representation and node-link diagram. Visual representation techniques allow engineers to make major decisions by providing meaningful representation of the design knowledge. Usually, these visualization techniques are designed for adept engineers, thus most visual representations tend not to cater to elementary engineers. Certain types of representation can be easier for novice engineers even though there is no difference for experts. For example, they can understand two distinguishable visualizations differently, even though both of them represent the same engineering design (Kleinmuntz & Schkade, 1993). Visualization gives challenges to users in that it has high complexity and many elements. The basic challenge is to present complex architecture of products in an understandable manner. Another mentionable issue is presenting engineering information in an easy scheme clearly without additional effort. Hence, visualization techniques should be studied to decide whether the chosen one is usable or not (Card, Mackinlay, & Shneiderman, 1999). Selecting appropriate information visualization techniques for engineering design by comparing and evaluating has several benefits:

- Improved engineering design: Constraints like time and money limit the number of iterations, which happen during engineering design. This can cause poor engineering design. Engineers are likely to skip choosing information visualization techniques with limited time. Proper information visualization technique leads to better engineering design that is not prone to failure.
- Reduced effort: Information visualization technique in itself may not have direct benefits for engineering design. However, from a user's point of view, working with a visualization tool which is easily understandable, accompanies improved productivity and requires less training effort. The time spent on considering information visualization techniques finally translates itself into a better design for engineering products or systems, which helps to get a better reputation.
- Minimizing engineering costs: Investigations on the importance of information visualization show that users can easily organize and analyze information and make decisions on complex tasks (Kelton, Pennington, & Tuttle, 2010; Speier, 2006; Zhang, 2008). Also, it is a communication tool among engineers to develop a deep understanding of engineering design. Proper information visualization techniques for engineering design can minimize unnecessary costs caused by misunderstanding and miscommunication.

To obtain the mentioned and other implicit benefits, we investigated which visualization technique is good in which engineering design context based on an extensive literature review. The rest of this paper is arranged as follows. Section 3 shows our user-study design. In the background study section, two visualization techniques for engineering design will be introduced. After that, a user study was conducted, and the results are explained and discussed. Finally, our research ends with a conclusion and future research ideas.

2. Literature review

Optimal visual information representation can be different depending on environment and purpose (Benbasat & Dexter, 1986; Benbasat, Dexter, & Todd, 1986; Coll, Coll, & Thakur, 1994; Tan & Benbasat, 1990; Vessey, 1991; Vessey & Galletta, 1991) because each one has its own granularity of abstraction, advantages, and disadvantages. Benbasat & Dexter assessed information presentation differences in user perceptions and decision making under various time constraints. Benbasat, Dexter, and Todd found usefulness differences in graphics according to tasks. Coll et al. considered the effects of four factors such as task type, education specialty, display presentation type, and task complexity in information visualization on user performance in 1994. Vessy and Galletta found that subjects chose the problem representation according to the task they received. Ellis and Dix mentioned challenging issues in evaluation of information visualization such as complexity, diversity, and measurement (Ellis & Dix, 2006). They argued complexity can be derived from interpretation that implies numerous assumptions and theoretical aspects and interaction mechanism between users and visualizations. They also pointed out diversity problem can be originated from variety of data and tasks, and individuality of people. They discussed measurement issue considering statistics, points of comparison and conditions.

2.1 Factors and metrics focused research

Over the past decade considerable research in information visualization has tried to compare or evaluate visualization techniques. Some researchers have mainly been interested in factors such as the criteria for comparison or evaluation of information visualization techniques. Wehrend and Lewis studied task-based comparisons of visualization tools that focused on identification and understanding the relationship of elements (Wehrend & Lewis, 1990). Sutcliffe et al. empirically evaluated two information visualizations which are a bullseye view and a hierarchical thesaurus by using usability metrics of user behavior, performance, and attitude (Sutcliffe, Ennis, & Hu, 2000). Luzzardi et al. suggested the term data usability with regard to information visualization techniques and applied interface usability as a barometer for the comparison of visualization techniques (Luzzardi et al., 2002). Some writer examined how familiarity can affect user performance by conducting hierarchy browser studies (Andrews, 2006). Lam studied interaction costs in information visualization as factors in visualization design (Lam, 2008). These were derived from selected 61 interaction-related usability issues in 484 researches. These consist of (1) decision cost for goals, (2) system-power costs for system operations, (3) multiple input mode costs for physical sequences, (4) physical-motion costs for execution of sequences, (5) visual-cluttering costs for perception state, (6), view-change costs for interpretation of perception, and (7) state-change costs for evaluation of interpretation. Some introduced cognitive perspectives for the evaluation of information visualization (Huang, Eades, & Hong, 2008). They attempted to find how and why the difference exists among visualizations that is not explained by measurement of the effectiveness for example, time and error rate. They proposed the research model that includes purpose-designed surveys, eye tracking, and cognitive load beyond time and error. O'Connell and Choong suggested heuristics-derived metrics in interactive visualization for analysts (O'Connell & Choong, 2008). Plaisant et al. performed systematic criteria development for the comparison of information visualization based on submitted reports in information visualization contests (Plaisant, Fekete, & Grinstein, 2008). Others noted human factor issues in information visualization and examined usage of human ability in terms of visualization with interactive rotatable visualization in large display (Robertson, Czerwinski, Fisher, & Lee, 2009). Scholtz proposed qualitative metrics and heuristics for an evaluation of visual analytic systems (Scholtz, 2010). Borkin and other researchers considered dimension issue in information visualization (Borkin et al., 2011). They evaluated and found 2D representation is easier, more efficient, and better than 3D representation to understand because all the data is seen at once. In view of all the research just mentioned, various factors can be considered in an overall evaluation.

Table 1. Summary of advantages and disadvantages of information visualization tools in terms of data attributes from (R Keller, Eger, Eckert, & Clarkson, 2005)

	DSM	Change risk plot	Propagation network	Propagation tree
Component connectivity	+/-	+/-	+	+/-
Propagation path	-	-	+/-	+

2.2 Evaluation or comparison methodology and / or framework-focused research

Much of the available literature on comparison or evaluation deals with framework. Amar and Stasko suggested gaps between representation and analysis and proposed a framework for evaluation and tasks to dwindle gaps (Amar & Stasko, 2004). Cook and Thomas examined a three-level evaluation model for visual analytics (Cook & Thomas, 2005). Saraiya et al. used insight-based methodology to evaluate gene microarray visualization tools (Saraiya, North, & Duca, 2005). They developed an evaluation method that measures user performance on predetermined tasks and defined insight as an individual observation about the data by the subject. Carpendale introduced various evaluation ways and explained edges and shortcomings of different approaches including quantitative and qualitative methods (Carpendale, 2008). The author suggested using methodologies that fit research situation with appropriate rigor. She proposed validity issues regarding conclusion, internal, construct, external, and ecological validity as challenges in quantitative methodologies. In addition, she mentioned sample size, subjectivity, and analysis issue as challenges in qualitative methods. Winckler et al. who viewed information visualization as a combination of visual representation and interaction proposed task-based evaluation scenarios for visualizing tools (Winckler, Palanque, & Freitas, 2004). Zuk et al. conducted a meta-analysis about selection and the systematization of heuristics for visualization evaluation (Zuk, Schlesier, Neumann, Hancock, & Carpendale, 2006). The concept of grounded evaluation was introduced by (Isenberg, Zuk, Collins, & Carpendale, 2008). They defined a process that considers the context of information visualization use as grounds for other specific visualization tools' evaluation and focused qualitative methods such as observation study as part of the design process and field studies. One study by Forsell and Johansson tried to apply heuristic evaluation in information visualization and proposed ten new heuristic sets (Forsell & Johansson, 2010). Shneiderman and Plaisant proposed a new methodology called Multi-dimensional In-depth Long-term Case studies (MILCs) for evaluation (Shneiderman & Plaisant, 2006). Moere et al. studied the effect of style in information visualization in terms of getting insights (Moere, Tomitsch, Wimmer, Christoph, & Grechenig, 2012). Altogether, these studies proposed and demonstrated new approaches for evaluation.

2.3 Benchmarking previous research

There are a few research studies that should be reviewed in detail because of close relevance to this study. Some authors evaluated readability of matrix-based representation and node-link diagram through seven tasks (Ghoniem, Fekete, & Castagliola, 2004). They found that matrix-based representation has advantages in most tasks such as node count and link count except in path finding. Node-link diagrams are preferred and more useful in path finding missions. They used artificially created data sets with variations of size and density. In their next research, they statistically demonstrated through these findings that matrix-based visualization is superior to node-link diagram in cases that have more than twenty nodes (Ghoniem, Fekete, & Castagliola, 2005). Keller et al. discussed which visualization is good for which sort of change propagation data and how visualization method can help change management among DSM, change risk plot, propagation network, and propagation tree (R Keller et al., 2005). Except propagation network, there is a disadvantage in other visualizations and propagation network may have shortcomings as shown in Table 1. They also have attempted to find which factor has significant influence on readability of Design Structure Matrix (René Keller, Eckert, & Clarkson, 2006). They considered three factors; size, density, and directionality. Also, they identified some tasks used in their experiment, for example, selecting a node or a link, counting the number of incoming/outgoing links and common neighbors, and finding the length of the shortest path. As they mentioned in their paper, the task in the experiment was not the task in engineering design process but just a simple information retrieval. They examined that finding the shortest path is the only task of the node-link diagram dominated matrix-based representation. It stays in line with Ghoniem et al.'s findings. Collectively, these investigations used data sets that are random or predetermined. This means users do not deal with real information but already visualized information, in other words, preprocessed information.

All of the studies reviewed here provide important insights. Even much of the current literature on comparison or evaluation of visualization has paid attention to various focuses. To the best of our knowledge, no systematic and empirical comparative evaluation of visualization techniques for engineering design has been carried out. The objective of this research is to answer the question of which visualization technique is better in certain engineering design contexts. Specifically, focused on understanding product architecture and engineering change, we compared matrix-based representation and node-link diagram. From previous investigations, we can suppose that matrix-based visualization is more suitable for understanding engineering design and node-link is more suitable for understanding engineering change.

Table 2. Selected comparison aspects in this research

Metric	Measurement	Description
Accuracy	Accuracy or error rate of completed tasks	Higher precision of visualization means a user is more likely to understand product architecture and engineering design changes.
Time duration	Time duration to complete tasks	The lower total time a user expended to use specific visualization technique means it is more efficient.
Familiarity	Background knowledge	If a user already knows theoretical knowledge about certain visualization tool, he/she can perceive that he is familiar with it.
	Practical experience	If a user already had experience of using certain visualization tools, he/she can perceive that he is familiar with it.
Work load	Cognitive load; assigned mental effort needed to perform tasks	If given visualization tools require much mental effort for a user, he/she can perceive it is difficult.

3. User study design

3.1 Background study of visualizations used in experiment

Relevant papers were reviewed from various journals and digital libraries. Investing an engineering product under different operating condition is a demanding task, because of the underlying complex interaction of elements within the product. To decode the element's interaction is the way to understand engineering changes in a product. Therefore, the obstacle remains to construe an engineering design in a methodical manner where only consequential relationships among key components are studied. In various situations, it is widely accepted that visualized graphs give a compendious way to define architecture and their interrelationships. Matrices and node-link diagrams are compendious and powerful techniques to represent enormous and tangled engineering design information. On the contrary, elaborate documentation can be so wordy that it takes more time to understand same information compared to graphical representation. In this paper, we experimented with two graphical tools to represent engineering design information, matrix-based visualization, and node-link diagram.

3.1.1 Node-link diagram

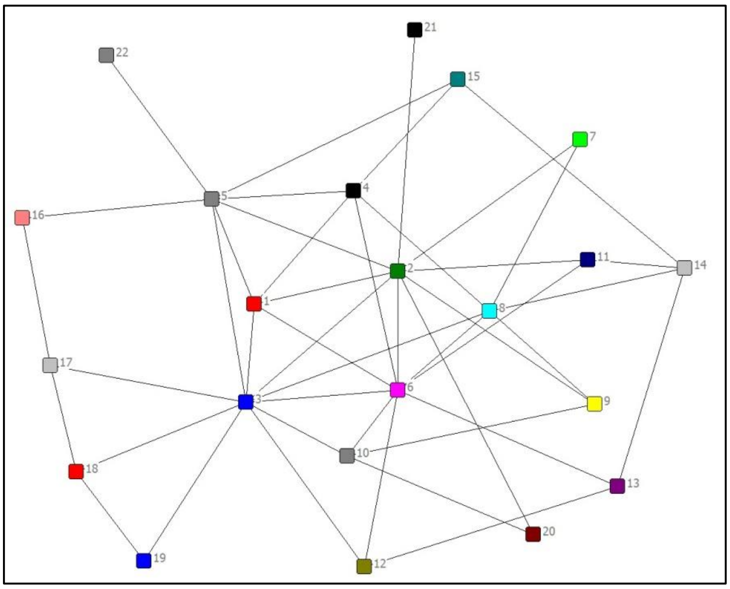

Figure 1. Node-link diagram of an engineering product

We can conceptually think of a product as a network; a set of vertices and edges between vertices. An element in the product can be represented as a node, and the interaction or dependency between elements can be represented as a link as shown in Figure 1. It is possible to express a node-link diagram in two-dimensional or three-dimensional spaces. A user can choose its layout in order to emphasize a particular facet of the engineering design. There is a large volume of literature describing node-link diagram layout algorithms (Battista, Eades, Tamassia, & Tollis, 1994; Kamada & Kawai, 1989). However, when a complex product is visually represented with node-link diagram, a user can perceive it as more complex because of overlapped nodes and links.

3.1.2 Matrix-based representation

	1	3	4	5	6	2	7	8	9	10	20	11	12	13	14	15	16	17	18	19	21	22
1		1	1	1	1	1																
3	1			1	1	1		1		1			1					1	1	1		
4	1			1	1			1								1						
5	1	1	1			1										1	1					1
6	1	1	1			1		1		1		1	1	1								
2	1	1		1	1		1		1		1	1									1	
7						1		1														
8		1	1		1		1		1						1							
9						1		1		1												
10		1			1				1		1											
20						1				1												
11					1	1									1							
12		1			1									1								
13					1								1		1							
14								1				1		1		1						
15			1	1											1							
16				1														1				
17		1															1		1			
18		1																1		1		
19		1																	1			
21						1																
22				1																		

Figure 2. Design Structure Matrix of an engineering product

One of the commonly used matrix-based representation tools for a complex system in the engineering field is adjacency matrices called design structure matrices (DSMs) (Browning, 2001; Eppinger, Whitney, Smith, & Gebala, 1994; Steward, 1981; Warfield, 1973). Warfield illustrated binary matrices for structural system modeling and transitivity that can be found by following the interconnection of subsystems and elements. Steward suggested matrix-based representation for the management of design iterations, reviews, and information flows. Eppinger et al. used matrix representation as a tool for the organization and management of relationship between product development tasks. Browning proposed DSMs as a system visual representation and analysis tool for an effective design of a complex system. A DSM shows elements ordered by rows and columns and their connections are indicated as filled cells in a square matrix. It has many advantages when a product is visually represented, for example, it can be rearranged by iterative transpositions of its rows and columns to grasp hidden substructure of the system and it does not have occlusion issues as shown in Figure 2. If there is an interaction between nodes, certain value is marked in an intersecting point of rows and columns, which are related nodes. According to research, domain and aspect values can be different; we can only express whether related nodes are connected or not with binary value, also we can only check how much material or information flows through this link. The fact that the matrix can be reordered can be very useful to a user (Siirtola & Mäkinen, 2005) in light of understanding hidden substructure by clustering (Browning, 2001). Yassine investigated how to use DSM as information communication tool that can represents task and information interdependency for complex engineering product projects (Yassine, 2004). Some researchers applied DSM to software domain to manage architecture of software system by analyzing code dependency (Sangal, Jordan, Sinha, & Jackson, 2005). Although, there is a limitation in the variety of matrix-based representation layouts due to the fact that elements should be horizontally and vertically ordered (Siirtola & Mäkinen, 2005).

3.2 Experiment procedure

To compare visualization techniques for engineering design, we chose accuracy, time duration, familiarity, and work load as comparison aspects as shown in Table 2. The number of user studies targeted to evaluate visualization techniques for engineering design was limited by the deficiency of an apt assessment method in the engineering design area. Which visualization technique is better for engineering design is dependent on knowing how an engineer interacts with and understands engineering information like the relationship of elements. Hence, echoing Fuhrmann and his colleagues (Fuhrmann et al., 2005), empirical study of the visualization tools can give insights into the capability of certain visualization and interaction mechanisms.

Among these various evaluation methods, we conducted a controlled experiment, a user study, to answer proposed research question following procedure as shown in Figure 3. We let participants decompose given engineering products and visualize their architecture. This process allows subjects to grasp directly the physical connectivity of real engineering products and transform it to visualization. It makes our experiment more practical and close to reality in that understanding the physical relationship of elements is a routine job in engineering design process. The screen-based test for the comparison or assessment of visualization is widely available, and has been used in many investigational studies (Ghoniem et al., 2004; Ghoniem et al., 2005; Huang, Eades, & Hong, 2009; René Keller et al., 2006). In this approach, during the screen-based test, it is possible to cause unintended bias because of several reasons.

- Someone can be very handy with the medium used for the test
- The usability of the medium can give direct and/or indirect impact on the usability of a visualization tool.
- The interface of the medium during engineering design use cannot be unified for each user.
- Resolution of the medium can also affect user performance.

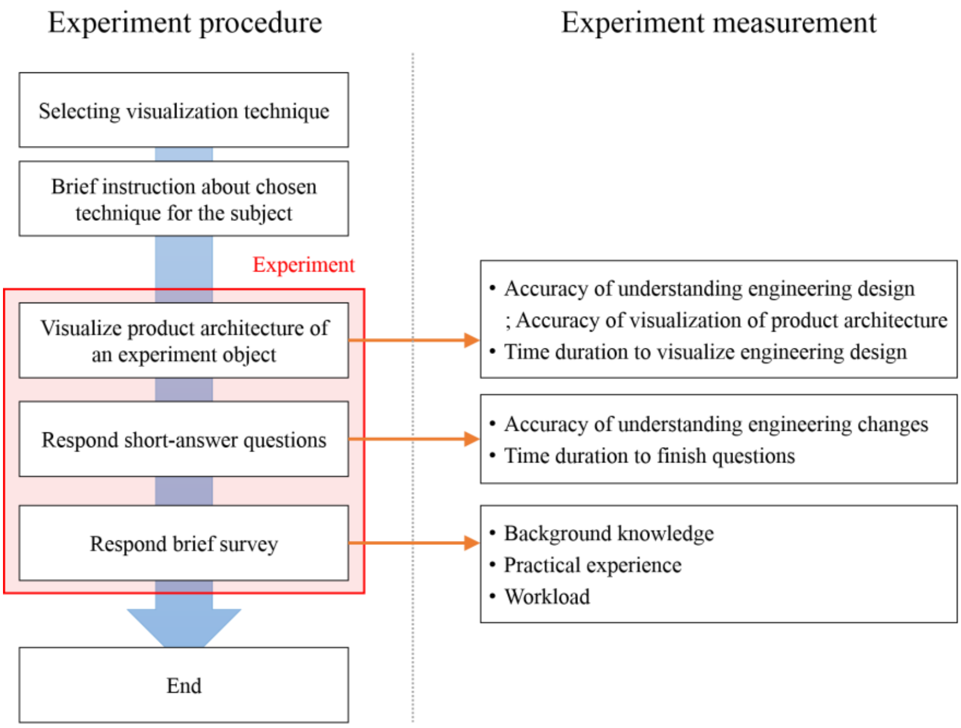

Figure 3. The experiment procedure

Accordingly, to avoid side effects of the used medium, we conducted a paper-based test to examine visualization techniques.

3.2.1 Participants

38 people took part in the experiment. The respondents were chosen among students in the engineering fields including mechanical engineering, industrial engineering, and computer science. 8 of them major in mechanical engineering, 10 computer science, and the rest major in industrial engineering. Undergraduate and graduate students were considered because they are candidates for elementary engineers who are not yet adroit at visualization techniques for engineering design. They have an intermediate level of background knowledge (3.26/5) and practical experience (3.11/5).

3.2.2 Experiment object

Architecture decomposition is the first step to analyze and manage products (Chiriac, Hölttä-Otto, Lysy, & Suh, 2011). Usually, when engineers deal with a product on an abstract level, at first granularity, the product is decomposed to 7±2 elements. 7±2 is appropriate in that people easily remember decomposed elements. The number originated from the research which discusses people's short-term and working memory capacity (Miller, 1956). On a more specific level, at second granularity, an architecture is handled with 25 ~ 81 elements, which is the square of 7±2. Among various engineering products, we selected irons because these have enough complexity to be an appropriate example of engineering design granularity as shown in Figure 4. Also, these are familiar to students, and these can show engineering design change. Detail of decomposed parts can be seen in Appendix A.

Figure 4. The dry iron (left) and steam iron with wire (right)

		1	3	4	5	6	2	7	8	9	10	20	11	12	13	14	15	16	17	18	19	21	22
BackCover	1		1	1	1	1	1																
BodyTop	3	1			1	1	1		1		1			1					1	1	1		
BodyBottom	4	1			1	1			1								1						
Electric_wire	5	1	1	1			1										1	1					1
Watertank	6	1	1	1			1		1		1		1	1	1								
TopCover	2	1	1		1	1		1		1		1	1									1	
Powersteam_Button	7						1		1														
Powersteam_Pump	8		1	1		1		1		1						1							
Spray_Button	9						1		1		1												
Spary_Pump	10		1			1				1		1											
Sprayhole	20						1				1												
SteamControl	11					1	1									1							
Selfclean_Button	12		1			1									1								
Selfclean_Part	13					1								1		1							
WaterTempCatridge	14								1				1		1		1						
Hotplate	15			1	1											1							
Bimetal	16				1														1				
Bimetal_Connector	17		1															1		1			
Thermostat_Dial	18		1																1		1		
Thermostat_Guide	19		1																	1			
Waterflap	21						1																
LED	22				1																		

Figure 5. DSM of a steamed iron with wire

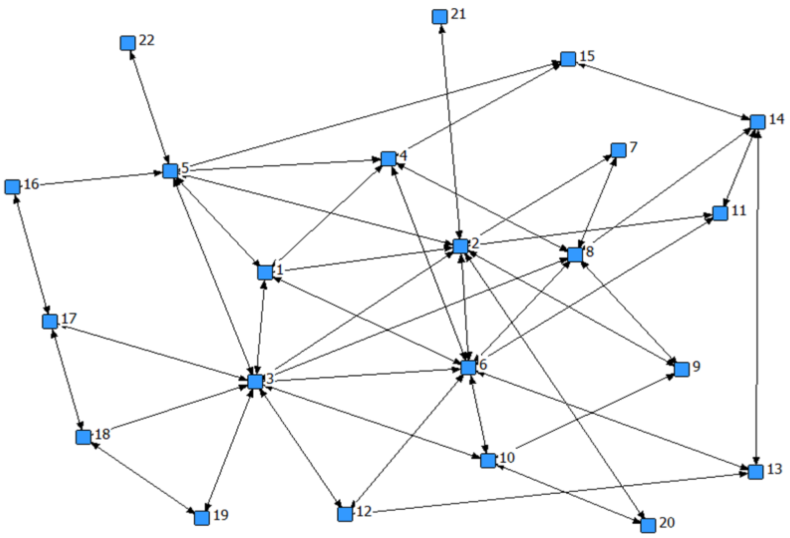

Figure 6. Node-link diagram of a steamed iron with wire

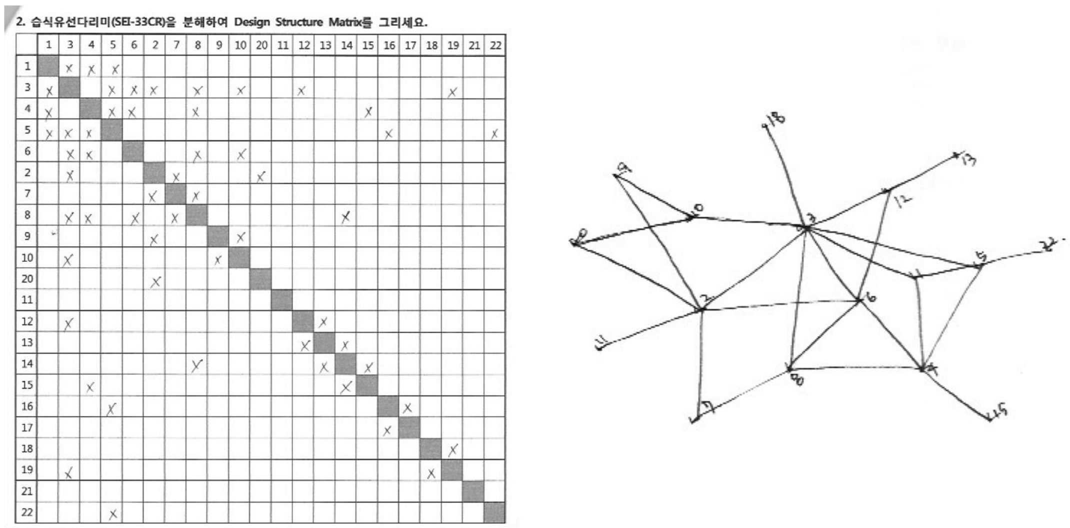

Figure 7. Samples of mapped product architecture by subjects with DSM (left) and node-link diagram (right)

3.2.3 Experiment procedure

Before the test, subjects received brief instruction on how to visualize with the selected techniques. Then they started the experiment. They had to draw and write down answers on paper sheets, and the time duration for each task was measured. The participants were required to visualize (i.e. map) an architecture of irons with selected visualization with decomposition like Figure 6 (task 1). This allowed them to understand product architecture by visualizing irons as shown in Figure 5. The used visualization tool was equally split between matrix-based representation (19 of 38) and node-link diagram. After they mapped two irons, to test whether they understand engineering design changes, they were asked to respond to short-answer questions. Before the survey, the participants received correctly marked architecture visualization to prevent the effect of incorrectly understood architecture visualization on tracing engineering change (task 2); 'Which components should you change and which elements are modified, if you want to infuse a new feature?' For instance, if a water cartridge is added on a dry iron, it leads to engineering design changes in several components. Components are coded by number and participants answered in figures. Used experiment sheets can be found in Appendix B.

3.2.4 Experiment measurement

How correctly they visualized the given product architecture was scored based on submitted sheets and how much time was spent to finish the task. When they missed the component or physical connection, it was considered inaccurate. Also, if they misinterpreted the suggested engineering change, it was considered inaccurate. There are 62 physical connectivities and 46 engineering changes that subjects should understand. Their background knowledge level and degree of practical experience were surveyed with a 5-point Likert scale to estimate their affinity with selected visualization technique. If a student marked 5 of 5, it means that he/she has very rich background knowledge (practical experience). Lastly, the participants reported how far mental effort was needed in the experiment for each task with a 9-point Likert scale. We used a rating scale to measure required mental effort. This methodology was assumed by Gopher and Braune and they proved subjects can numerically express their mental load by themselves (Gopher & Braune, 1984). Paas demonstrated this finding in the context of cognitive load theory in 1992 (Paas, 1992).

4. Result and discussion

4.1 Descriptive statistics analysis

We used R Program and Excel to analyze the data collected by the experiment. Table 3 gives the mean value of accuracy, time duration, and workload. Among these measures, the main performance measures for comparative evaluation are the rate of accurate answers and the time to complete tasks. All statistical difference tests about descriptive statistics were done in the significant level of 0.05. There is no statistical difference in familiarity of visualization between participants as shown in Table 4. The user who had more background knowledge showed better performance in understanding engineering design and changes and took less time duration to understand engineering design. The user who had more practical experience showed better performance in understanding engineering changes and took less time duration to understand engineering changes. The results of the descriptive statistical analysis are shown Table 5. Detail of experiment result can be found in Appendix C.

As we expected, DSM is more useful for understanding engineering architecture whereas node-link diagram is more powerful for understanding engineering change. Considering accuracy, it can be seen from Table 5 that students mapped product architecture more correctly with DSM, compared to node-link diagram (Figure 11 and 12). Regarding the tracking of engineering change, there is no difference in usefulness between two visualizations (Figure 13 and 14). In regard to time, the node-link diagram took less time to understand engineering design and change respectively, in the significant level of 0.05, 0.01.

Table 3. Means of accuracy, time duration, and workload

	Understanding Engineering Design		Understanding Engineering Change	
	DSM	Node-link diagram	DSM	Node-link diagram
Accuracy (%)	85.11	79.95	78.96	81.94
Time (min.)	37.47	33.89	14.84	12.05
Workload	5.32	4.00	5.74	4.21

Table 4. Statistical difference between two visualizations for familiarity

Familiarity	Visualization	Mean	SD	t-value	p-value
Background Knowledge	DSM	3.11	1.15	-0.29	0.39
	Node-link diagram	3.21	1.08		
Practical Experience	DSM	3.00	0.82	-0.57	0.29
	Node-link diagram	3.21	1.40		

Table 5. Statistical difference between DSM and Node-link diagram for accuracy and time duration

	Visualization	Mean	SD	t-value	p-value
Accuracy of Understanding Engineering Design (AUED) (%)	DSM	84.89	9.06	1.76	0.04*
	Node-link diagram	79.63	9.35		
Accuracy of Understanding Engineering Change (AUEC) (%)	DSM	73.00	9.35	-0.99	0.16
	Node-link diagram	75.74	7.64		
Time duration to Understand Engineering Design (TUED) (min.)	DSM	37.47	4.99	2.07	0.02*
	Node-link diagram	33.89	5.65		
Time duration to Understand Engineering Change (TUEC) (min.)	DSM	14.84	3.75	2.47	0.01**
	Node-link diagram	12.05	3.17		

* $p \leq 0.05$; ** $p \leq 0.01$.

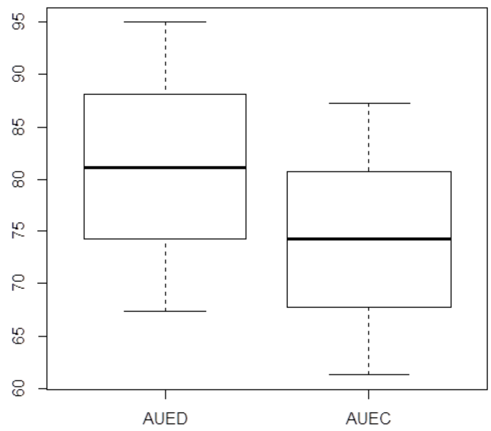

Figure 8. Distribution of AUED and AUEC

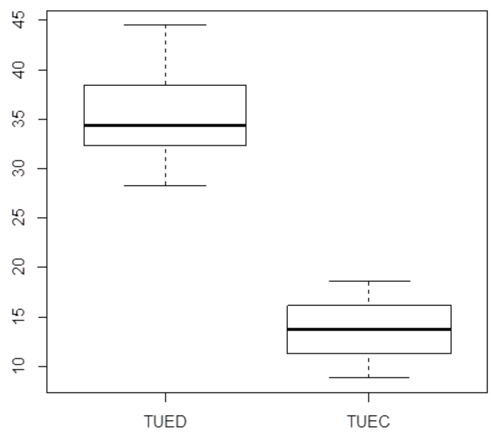

Figure 9. Distribution of TUED and TUEC

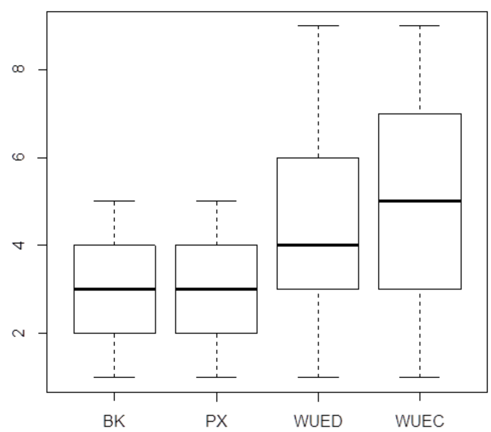

Figure 10. Distribution of BK, PX, WUED, and WUEC

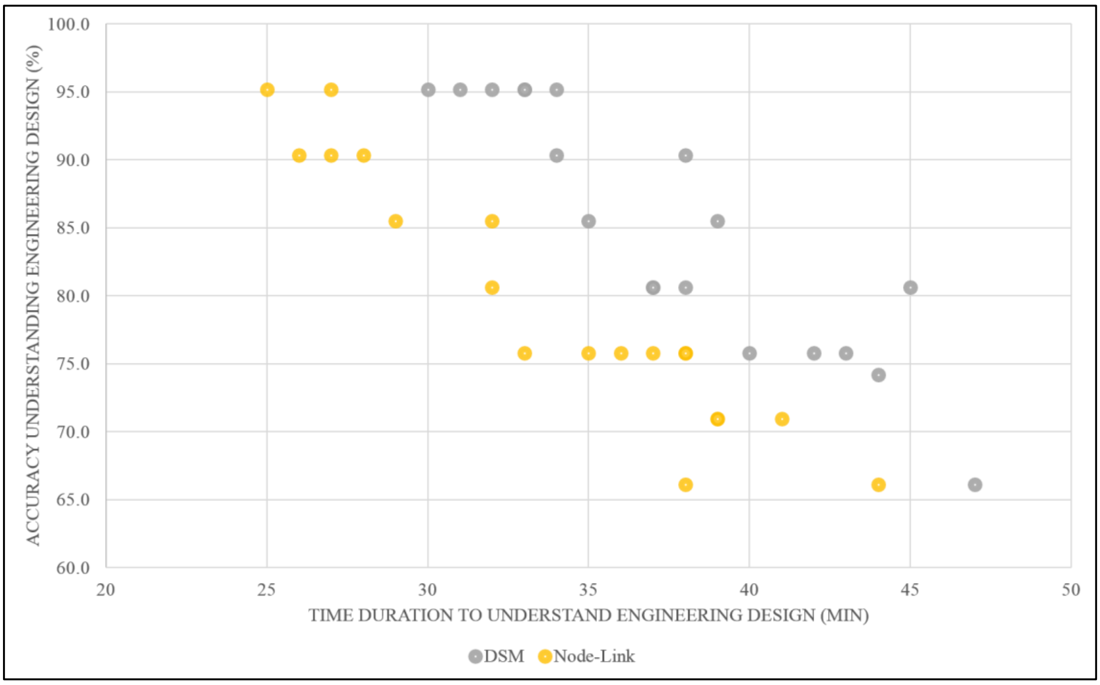

Figure 11. Accuracy of Understanding Engineering Design by Time duration to Understand Engineering Design

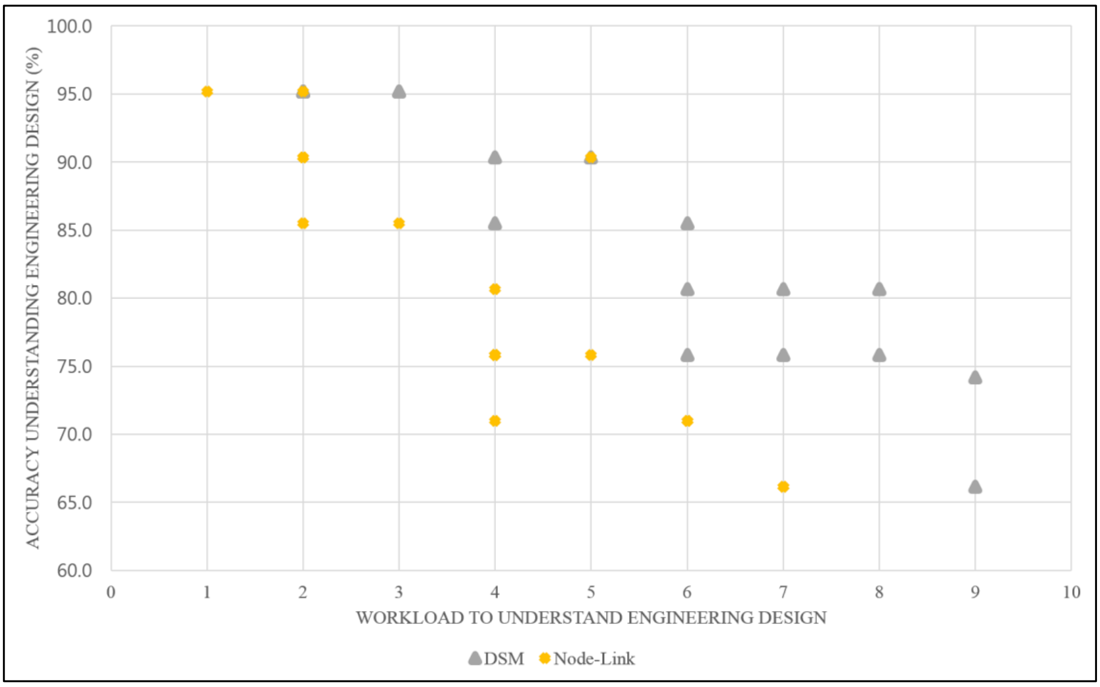

Figure 12. Accuracy of Understanding Engineering Design by Workload to Understand Engineering Design

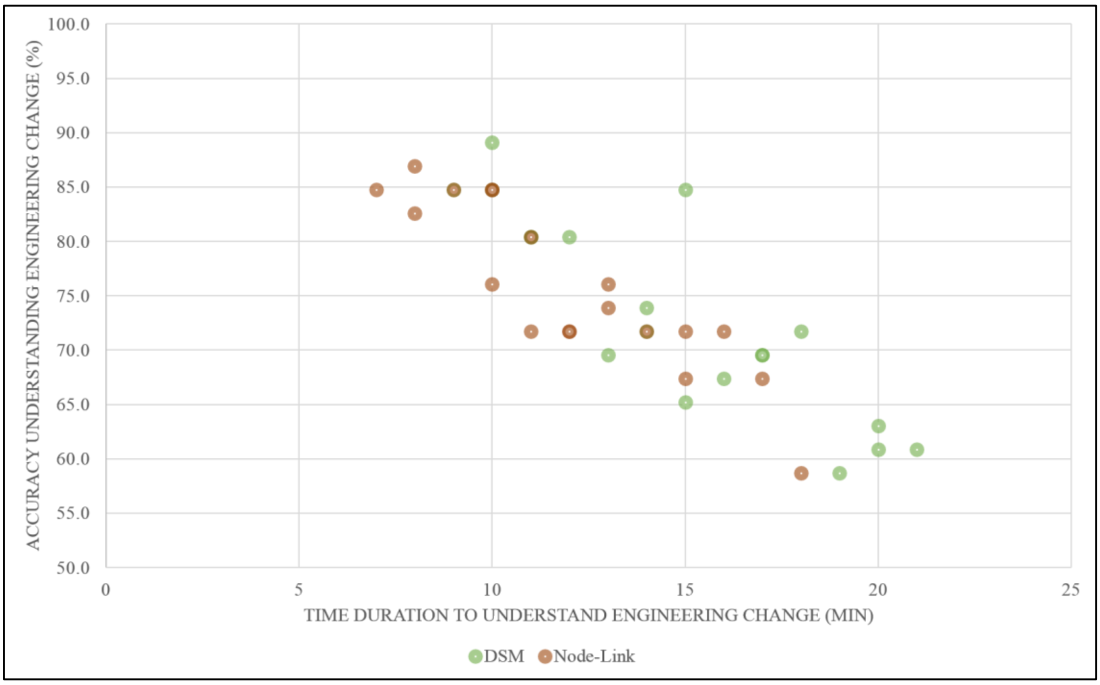

Figure 13. Accuracy of Understanding Engineering Change by Time duration to Understand Engineering Change

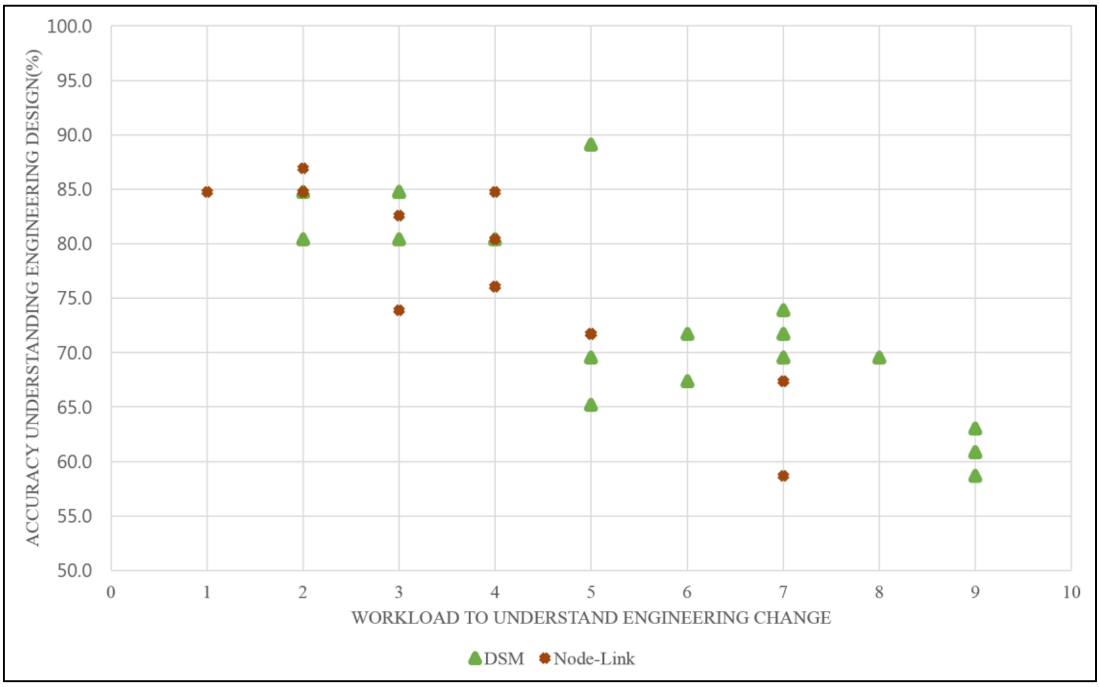

Figure 14. Accuracy of Understanding Engineering Change by Workload to Understand Engineering Design

Box-plot diagrams shows distribution of measured experiment data. In Figure 7, y-axis represents accuracy of understanding engineering design and engineering change in percentage. Y-axis in Figure 8 represents the answer time in minutes to finish each task. In Figure 9, y axis represents surveyed score for each question.

4.2 Visualization efficiency analysis

An approach to compute measures of costs such as time duration and workload with measures of task performance can be used to compare efficiency of visualizations. As you can see the model in Figure 11, we compared visualization efficiency for engineering design use concerning devoted cost (time duration and workload) and performance (accuracy). Data envelopment analysis (DEA) was developed by Charnes et al. (Charnes, Cooper, & Rhodes, 1978). It is a relative performance, productivity, or efficiency measurement methodology which considers multiple inputs and outputs and is applied to various fields involving service organizations, manufacturing and others (Coelli, Rao, O'Donnell, & Battese, 2005; Talluri, 2000). Aristovnik et al. measured the relative efficiency of police activities regarding invested budget (Aristovnik, Seljak, & Mencinger, 2014). Metzger applied it to measure efficiency of branch offices (Metzger, 1994) and Byrnes et al. analyzed technical efficiency in strip mining (Byrnes, Färe, & Grosskopf, 1984). In such ways, specific visualization can be considered more efficient when the associated performance is higher than expected on the basis of invested costs, for example, when time and workload are equivalent or when a subject’s cost is lower than expected considering performance. Within the participants’ limited capacity, they can maintain performance constantly by investing more effort even when the task requires more time and workload. Specifically, the time and workload cannot be continually assumed from performance-based measures. However, the combination of measures of time, workload and performance can show meaningful information about visualization, which is not always found by performance and time or workload alone.

Visualization efficiency can be defined as (1) regarding various inputs and outputs. If we assume that there are n subjects’ efficiency scores, each with m costs and s performances, then we can find the relative visualization efficiency score of subject x by solving the fractional linear programming model as below. We notated relative visualization efficiency of subject x as e_x, efficiency can be described like (2). To maximize visualization efficiency, we have to maximize the model below.

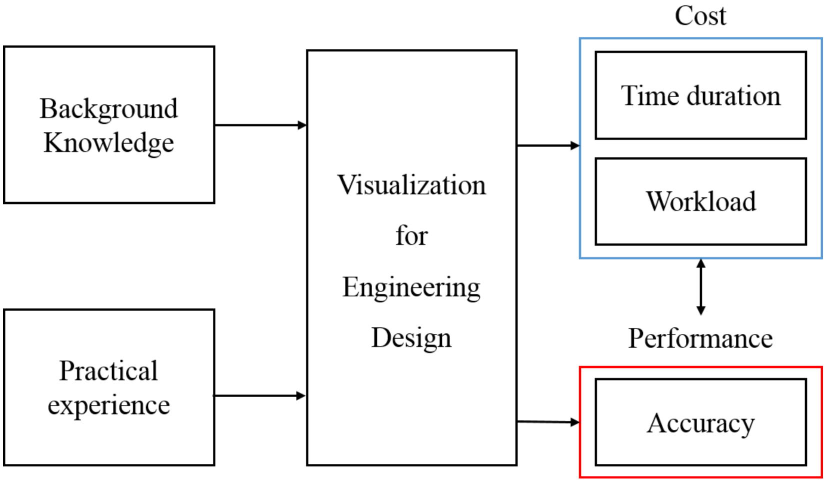

Figure 15. Visualization Performance-Cost model

$$\text{Visualization Efficiency} = \frac{\textit{weighted sum of performances}}{\textit{weighted sum of costs}} \qquad (1)$$

$$e_x = \frac{\sum_{k=1}^{s} v_k P_{kx}}{\sum_{j=1}^{m} u_j C_{jx}} \qquad (2)$$

$$\text{Max} \;\; e_x = \frac{\sum_{k=1}^{s} v_k P_{kx}}{\sum_{j=1}^{m} u_j C_{jx}} \qquad (3a)$$

$$\text{s.t} \;\; \frac{\sum_{k=1}^{s} v_k P_{ki}}{\sum_{j=1}^{m} u_j C_{ji}} \leq 1 \;\; \forall\, i \qquad (3b)$$

$$v_k, u_j \geq 0 \quad \forall\, k, j,$$

where

k = 1 to s, performance index,

j = 1 to m, cost index

i = 1 to n, subject index

$P_{ki} = \textit{Performance K done by subject i}$

$v_k = \textit{weight given to Performance k}$

$u_j = \textit{weight given to Cost j}$

P_{kx} means the amount of performance k conducted by subject x, and C_{jx} refers to the amount of cost j devoted by subject x. v_k presents weight value given to performance k, and u_j provides weight value given to cost j. s is the number of performances. In our model $s = 2$, and m represents the number of costs, in our model, $m = 2$. Without additional constraint, we cannot solve (3a) (because it is unbounded) hence technical constraints (3b) that weighted the sum of inputs (costs) should be less than or equal to the weighted sum of outputs (performances) is inserted.

We normalized the sum of the weighted costs which is the denominator of (3a) to 1 and it can be seen in (4) because it is difficult to solve this kind of fractional linear programming model. The fractional model can be transformed to a linear programming model as below. To find the visualization efficiency score for each participant, we solved the below optimization formulation for n times. Theoretically, every time duration and workload weights are defined to maximize each efficiency score. If a score is 1, it means this visualization is efficient unless that visualization is relatively inefficient.

$$\text{Max} \sum_{k=1}^{s} v_k P_{kx}$$

$$\text{s.t} \quad \sum_{j=1}^{m} u_j C_{ji} = 1 \qquad (4)$$

$$\sum_{k=1}^{s} v_k P_{ki} - \sum_{j=1}^{m} u_j C_{ji} \leq 0 \quad \forall\, i$$

$$v_k, u_j \geq 0 \quad \forall\, k, j$$

By solving the aforementioned formulation, we got the visualization efficiency scores that are summarized in Table 7.

Table 6. Visualization efficiency by task

Task	Visualization	Mean	SD	t-value	p-value
Understanding Engineering Design	DSM	0.61	0.14	-0.63	0.27
	Node-link diagram	0.65	0.19		
Understanding Engineering Change	DSM	0.45	0.17	-2.00	0.03*
	Node-link diagram	0.57	0.21		
Understanding Engineering Design & Change	DSM	0.63	0.16	-1.19	0.12
	Node-link diagram	0.70	0.19		

* $p \leq 0.05$

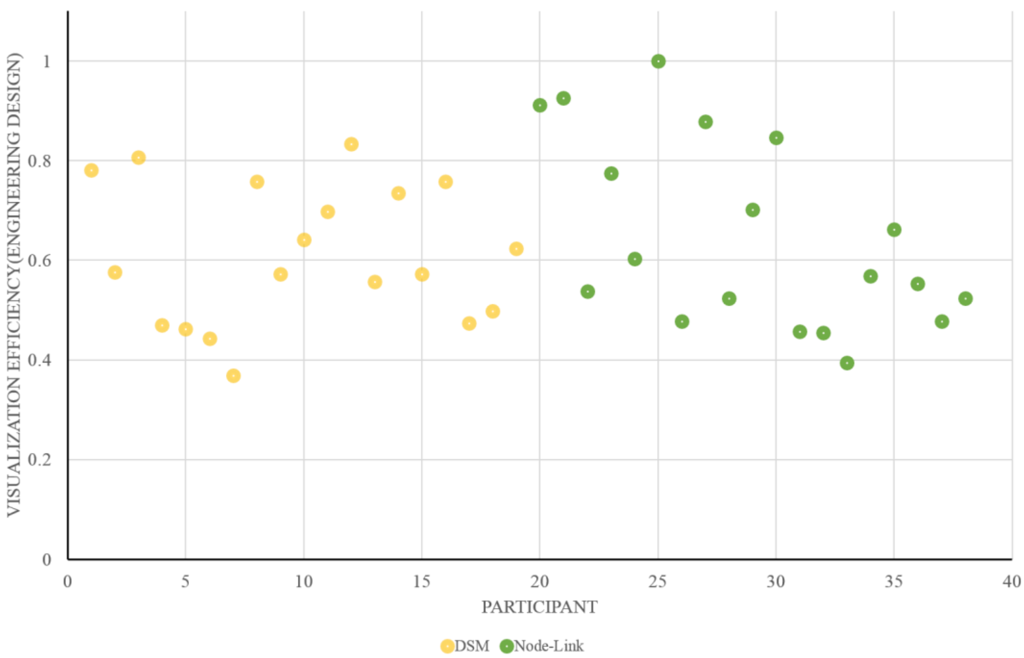

Figure 16. Visualization Efficiency in Understanding Engineering Design

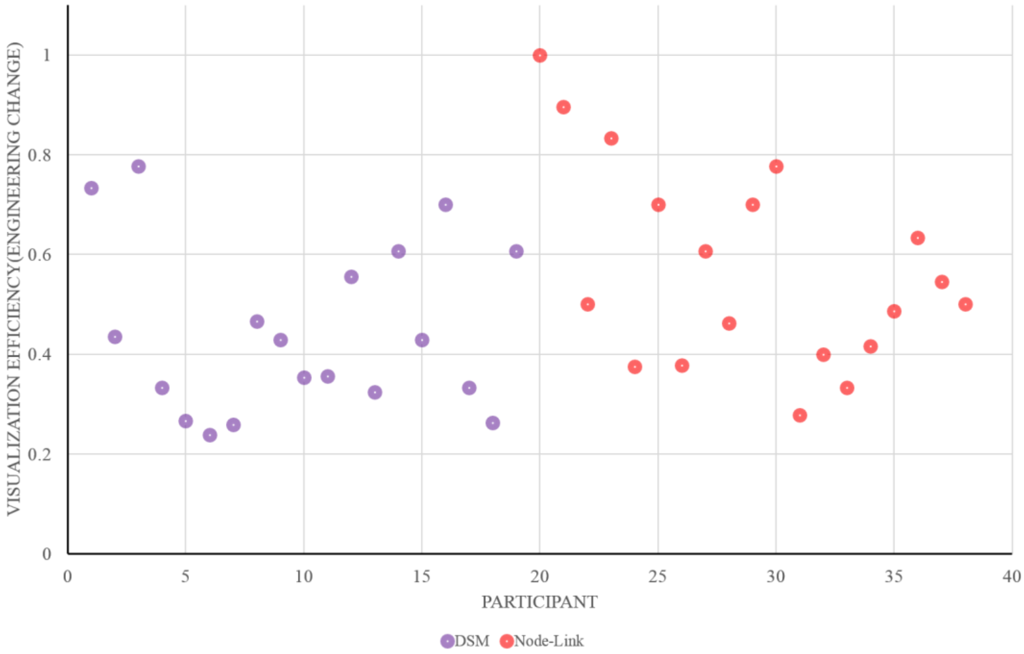

Figure 17. Visualization Efficiency in Understanding Engineering Change

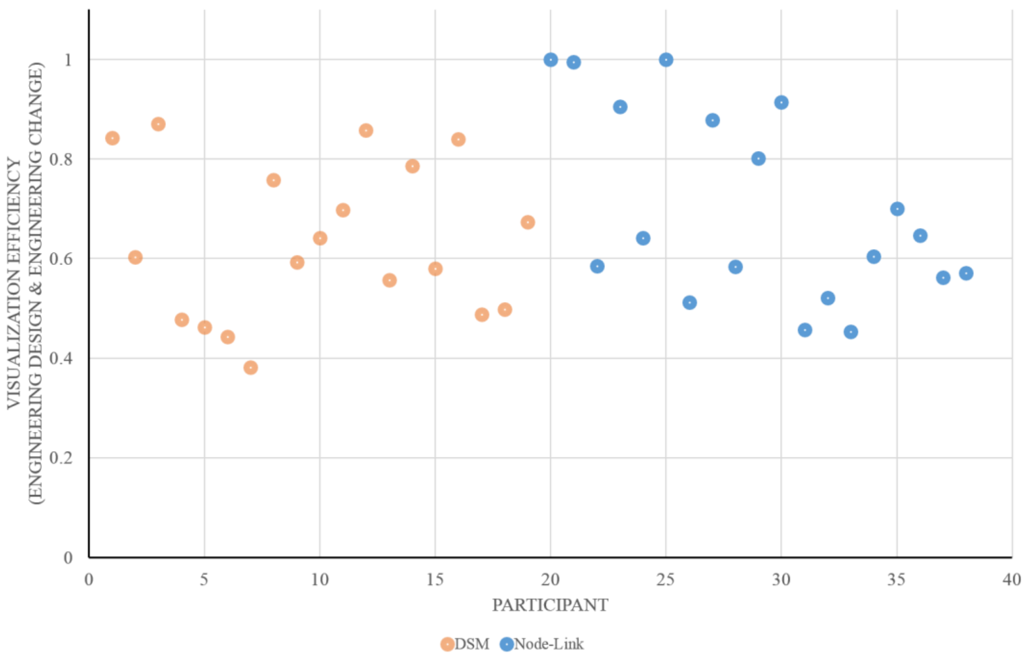

Figure 18. Visualization Efficiency in Understanding Engineering Design and Engineering Change

Table 7. Sample of measured experiment data and visualization efficiency score

Subject No.	Visualization	WUED	WUEC	TUED (min)	TUEC (min)	AUED (%)	AUEC (%)	Visualization Efficiency on Engineering Change
12	DSM	2	2	30	12	95.2	80.4	0.55
13	DSM	8	6	38	18	80.6	71.7	0.33
22	Node-link	4	5	37	12	75.8	71.7	0.49
27	Node-link	5	4	27	11	90.3	80.4	0.60

WUED: Workload to Understand Engineering Design

WUEC: Workload to Understand Engineering Change

TUED: Time duration to Understand Engineering Design

TUEC: Time duration to Understand Engineering Change

AUED: Accuracy of Understanding Engineering Design

AUEC: Accuracy of Understanding Engineering Change

The efficiency analysis shows that the node-link diagram is more efficient than DSM when it's used for understanding engineering change (see Table 6 and Figure 16), even two visualizations have no statistical difference in efficiency when they are used for understanding engineering design (see Table 6 and Figure 17). When we considered altogether engineering design and changes, there was no meaningful difference in visualization efficiency (see Table 6 and Figure 18). There is sample of measured experiment data and visualization efficiency scores in Table 7. For example, subject 12 and 27 showed the same accuracy of grasping engineering change but we can check that subject 27's visualization efficiency score is higher than subject 12's. Simultaenously, we can recognize that node-link diagram is more efficient than DSM on tracking engineering changes in that subject 22 has a higher visualization efficiency score than subject 13 even though they both have the same accuracy. Considering same performance done by subjects, node-link diagram is efficient at low costs, time, and workload. Some of the participants responsed that node-link diagram is more usable in the way that users can intuitively trace change propagation following links. This result is fully supported by previous research done by many authors (R Keller et al., 2005) and (Ghoniem et al., 2004; Ghoniem et al., 2005; René Keller et al., 2006) who handled similar tasks like finding paths. DSM requires users to expend more concentration when it forces them to double-check elements in both rows and columns.

4.3 Discussion

Information visualization in engineering design process is a continuous, iterative, and interactive interface which asks time, workload, clarity, granularity, and results. It is continuously used to find relavancy among elements and is included in every design and decision making process. Likewise, it is continuously and repeatedly used during engineering design processes to interact with engineering information and other engineers, designers, and stakeholders. Engineers repeatedly examine intermediate findings and outputs and the overall cycle through visualizing tools during the design process. Without adequate visualization tools, engineers can show poor performance due to the limitation of human vision and cognition that causes incomprehension derived from abstractness of engineering information. Engineers should carefully select visualization tools via comparison or evaluation because it not only assists design process but requires workload itself. People use their perceptual and cognitive system to understand information visualization which implies knowledge and hidden insights. They can lessen the workload but situationally improper visualization could rather cause adverse effects that disturb primary design tasks. Visualization techniques are not regarded as the ultimate engineering design goal. They should be designed with clarity and granularity, which refers to the amount of related elements visualized to guide engineers to productive outputs.

In this study, our main focus was functionality, effectiveness (accuracy, in other words, how completely users accomplish certain tasks) and efficiency(invested resources such as time and workload in considering effectiveness). Information visualization in engineering design offers us a basement to get design knowledge and insights beyond abstractness of engineering data and information so engineers can explore and extract necessary information for design process by using visualization techniques. On the basis of comparative evaluation studies on the visualization tools for engineering design purpose, it can be assumed that visualization tool contributes to make better decisions because it reduces or eliminates the risk of doing a faulty analysis during design process.

The reason why we use information visualization tools is to get knowledge from engineering information more effectively and efficiently. We considered a few factors for the comparative study. This pragmatic evaluation offers experiment procedures that can be easily implemented to other domains because the exemplified factors and experiment procedure are domain independent. However, there are some challenges in our research:

- It requires a considerable time for both participants and experimenters to do disassembling and mapping tasks and to grade answers.
- More motivated and adroit participants are needed. It would seem that subjects were demotivated during the study because most of them were not domain experts.
- Longer visualization usage time can lead users to reveal more practical usage patterns.

First, it took significant time for participants to disassemble the given engineering products. Although this task made them break down objects and understand the product structure by themselves, people who were not familiar with it became exhausted. Second, the users had only an intermediate level of familiarity of visualization tools but how far they were familiar with engineering design projects was not determined. Domain familiarity can affect user performance because familiarity of visualization methods had meaningful effects on accuracy and time duration of given tasks. Third, the experiment was conducted within less than one hour for each subject. Engineering designers and system architects face engineering information for several days and weeks even more than one year in their routine work. User performance and visualization efficiency can be different in long-term periods.

5. Conclusion

Any tool which an engineer uses should operate as a user intended in their task (useful), and be easy to use and learn (Gould & Lewis, 1985). For engineers, understanding product structure and tracing modification during engineering design is a challenging exercise that requires much time. The importance of this article is that it started the initial stage in a comparative evaluation of information visualization for engineering design use. The ability of information visualization in engineering design has not been fully investigated. It is not yet known whether it could boost decision-making or it could interfere with its original purpose. Based on such a research methodology, typical visualization techniques for engineering design can be compared.

Simple engineering product examples were used as an experiment object that was not difficult to participants. We considered understanding both architecture and engineering change tasks because engineering design usually includes both understanding architecture and exploring the relationship of elements. In the current study, comparing DSM with node-link diagram showed that specific visualization tools are better and more efficient in certain engineering design tasks. This findings suggest that DSM is useful for grasping product architectrue, while node-link diagram is better for tracing engineering design change. According to the task situation, differences in accuracy between visualization techniques were found in understanding architecture tasks. Also, we found that certain visualizations are more efficient in particular engineering design tasks.

We compared visualization efficiency through a data envelopment analysis, which is used to measure relative efficiency and productivity. Economics in engineering design process is important because design process is usually conducted under time constraints and limited human and other resources. We expect that this economic analysis can be more reasonable than previous analysis in that the comparison purpose of decision makers can be reflected with flexibility.

We anticipate that this sort of result can be more effective with experts, because engineering designers have implied and goal-dependent knowledge of their own design. This kind of result may be more effective using certain visualization techniques which is better with their particular circumstances. Researchers and engineers using visualization techniques may benefit from the discussion learned in this article. Understanding and analyzing architecture and data sets that are representative of practice is difficult in all engineering domains. Although this is true for information visualization comparison, researchers developing and investigating visualization tools for engineering design can refer to the tasks and procedures used in this paper. Detailed study design including tasks can be adjusted for other tools and their purpose.

Engineers tend to use visualization techniques pre-determined by colleagues. We should investigate visualizing tools that we habitually use in engineering design in various perspectives, for instance, human-computer interaction, user interface, knowledge retrieval, and information design. More broadly, research is also needed to consider other factors in visualization that may impact user performance and visualization efficiency. Domain fitness and aesthetic aspects of information visualization techniques, for example, can make a difference in experiment results. By doing a contextual interview as a qualitative research tool with participants, researchers can glean other insights which are not expressed in numerical experiment results. Subjects can describe the demanding issues in current work processes and environments when they use information visualization tools for engineering design purposes. Future research might explore reliability focused comparisons or evaluations. Reliability of information visualization implies how much it can endure different domain ranges of engineering information and various data complexities such as dimension issues. By resolving these issues, information visualizations can be improved for more efficient engineering design.

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Appendix

Appendix – A. Detail of decomposed irons

Decomposed iron parts were numerically coded for participants who are not familiar with iron parts. In the experiment, subjects used these figure instead of the name of parts.

A-1. Dry iron (SEI-10DS)

Table 8. Configuration of dry iron

SEI-10DS Configuration	Number
BackCover	1
TopCover	2
BodyTop	3
BodyBottom	4
Electric_wire	5
Hotplate	6
Bimetal	7
Thermostat Dial	8
LED	9

Figure 19. Decomposed Dry iron (SEI-10DS)

A-2. Steam iron (SEI-33CR)

Table 9. Configuration of steam iron

SEI-33CR Configuration	Number	SEI-33CR Configuration	Number
BackCover	1	Selfclean_Button	12
TopCover	2	Selfclean_Part	13
BodyTop	3	WaterTempCatridge	14
BodyBottom	4	Hotplate	15
Electric_wire	5	Bimetal	16
Watertank	6	Bimetal_Connector	17
Powersteam_Button	7	Thermostat_Dial	18
Powersteam_Pump	8	Thermostat_Guide	19
Spray_Button	9	Sprayhole	20
Spary_Pump	10	Waterflap	21
SteamControl	11	LED	22

Figure 20. Decomposition of steam iron (SEI-33CR)

Appendix – B. Experiment sheets

Participants were asked to map product architecture with DSM or node-link diagram. They visualized irons' architecture according to configuration in Appendix A. Those who used DSM mapped iron in matrix sheets as below. The others who used node-link diagram mapped iron in empty paper. After that, they were required to answer questions from 3 to 7 to check whether they understood engineering change. Finally, subjects answered survey for workload, background knowledge, and practical experience.

1. Decompose dry iron (SEI-10DS) and map product architecture with Design Structure Matrix

	1	2	3	4	5	6	7	8	9
1									
2									
3									
4									
5									
6									
7									
8									
9									

2. Decompose steam iron (SEI-33CR) and map product architecture with Design Structure Matrix

	1	3	4	5	6	2	7	8	9	10	20	11	12	13	14	15	16	17	18	19	21	22
1																						
3																						
4																						
5																						
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22																						

3. Which components should be added to insert spray function?

3-1. Which components should be redesigned because of change propagation by spray function?

4. Which components should be added to insert power steam function?

4-1. Which components should be redesigned because of change propagation by power steam function?

5. Which components should be added to insert self-clean function?

5-1. Which components should be redesigned because of change propagation by self-clean function?

6. To make an iron that has separable water tank, which components should be changed, and which components should be redesigned because of propagation by change?

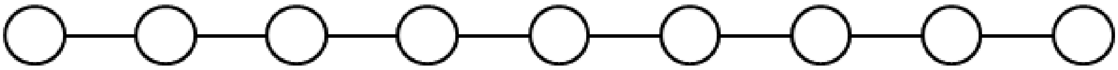
7. To make wireless steam iron, which components should be changed, and which components should be redesigned because of propagation by change?

Survey

Workload

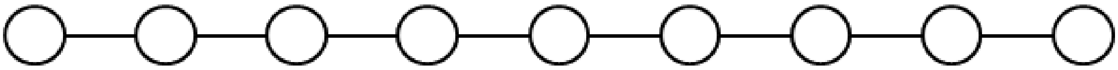
1. How difficult to understand engineering design with used visualization technique?

Easy to understand | Difficult to understand



2. How difficult to understand engineering change with used visualization technique?

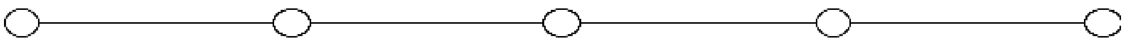
Easy to understand | Difficult to understand



Background knowledge / Practical experience

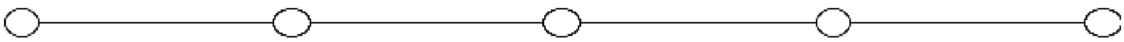
1. How much background knowledge do you have about used visualization technique?

Weak theoretical knowledge | Strong theoretical knowledge



2. How frequently use selected visualization technique in your research or work?

Never use | Every day



Appendix – C. Experiment result

Table 20 shows the number of correct answers and converted accuracy to percentage.

Table 10. Experiment result 1/2

No.	Visualization	Accuracy of Understanding Engineering Design (0~100)	Accuracy of Understanding Engineering Change (0~100)	The number of Correct answer ED	The number of Incorrect answer ED	The number of Correct answer EC	The number of Incorrect answer EC
1	DSM	95.2	89.1	59	3	41	5
2	DSM	85.5	69.6	53	9	32	14
3	DSM	95.2	84.8	59	3	39	7
4	DSM	80.6	69.6	50	12	32	14
5	DSM	75.8	63.0	47	15	29	17
6	DSM	74.2	60.9	46	16	28	18
7	DSM	66.1	60.9	41	21	28	18
8	DSM	95.2	84.8	59	3	39	7
9	DSM	80.6	73.9	50	12	34	12
10	DSM	85.5	67.4	53	9	31	15
11	DSM	90.3	65.2	56	6	30	16
12	DSM	95.2	80.4	59	3	37	9
13	DSM	80.6	71.7	50	12	33	13
14	DSM	95.2	80.4	59	3	37	9
15	DSM	80.6	71.7	50	12	33	13
16	DSM	95.2	84.8	59	3	39	7
17	DSM	75.8	69.6	47	15	32	14
18	DSM	75.8	58.7	47	15	27	19
19	DSM	90.3	80.4	56	6	37	9
20	Node-Link	90.3	84.8	56	6	39	7
21	Node-Link	95.2	87.0	59	3	40	6
22	Node-Link	75.8	71.7	47	15	33	13
23	Node-Link	85.5	82.6	53	9	38	8
24	Node-Link	75.8	71.7	47	15	33	13
25	Node-Link	95.2	84.8	59	3	39	7
26	Node-Link	71.0	67.4	44	18	31	15
27	Node-Link	90.3	80.4	56	6	37	9
28	Node-Link	75.8	73.9	47	15	34	12
29	Node-Link	85.5	84.8	53	9	39	7
30	Node-Link	90.3	84.8	56	6	39	7
31	Node-Link	66.1	58.7	41	21	27	19
32	Node-Link	71.0	71.7	44	18	33	13
33	Node-Link	66.1	67.4	41	21	31	15
34	Node-Link	75.8	71.7	47	15	33	13
35	Node-Link	80.6	76.1	50	12	35	11
36	Node-Link	75.8	76.1	47	15	35	11
37	Node-Link	71.0	71.7	44	18	33	13
38	Node-Link	75.8	71.7	47	15	33	13

Table 11. Experiment result 2/2

No.	Visualization	Time to Understand Engineering Design (min)	Time_to_Understand Engineering Change (min)	Background Knowledge (1~5)	Practical Experience (1~5)	Workload to Understand Engineering Design (1~9)	Workload to Understand Engineering Design (1~9)
1	DSM	32	10	4	4	3	5
2	DSM	39	13	2	3	4	5
3	DSM	31	9	4	4	3	2
4	DSM	45	17	3	3	8	8
5	DSM	43	20	2	2	8	9
6	DSM	44	21	2	1	9	9
7	DSM	47	20	1	2	9	9
8	DSM	33	15	5	4	2	3
9	DSM	37	14	2	3	6	7
10	DSM	35	16	3	3	6	6
11	DSM	34	15	4	3	5	5
12	DSM	30	12	4	3	2	2
13	DSM	38	18	3	3	8	6
14	DSM	34	11	4	4	2	3
15	DSM	37	14	2	3	7	7
16	DSM	33	10	5	4	2	3
17	DSM	42	17	3	3	6	7
18	DSM	40	19	2	2	7	9
19	DSM	38	11	4	3	4	4
20	Node-Link	26	7	4	5	2	1
21	Node-Link	27	8	5	5	2	2
22	Node-Link	37	12	3	3	4	5
23	Node-Link	29	8	4	4	2	3
24	Node-Link	33	16	3	2	4	5
25	Node-Link	25	10	5	5	1	2
26	Node-Link	39	15	2	1	6	7
27	Node-Link	27	11	2	2	5	4
28	Node-Link	38	13	3	4	4	3
29	Node-Link	32	10	4	5	3	4
30	Node-Link	28	9	5	5	2	2
31	Node-Link	38	18	2	2	7	7
32	Node-Link	41	15	2	3	4	5
33	Node-Link	44	17	2	1	7	7
34	Node-Link	35	14	3	2	5	5
35	Node-Link	32	13	4	3	4	4
36	Node-Link	36	10	3	4	4	4
37	Node-Link	39	11	2	3	6	5
38	Node-Link	38	12	3	2	4	5

Measured time duration and survey result can be found in Table 11.

Abstract

이 연구의 목적은 공학 설계와 그 변경을 이해하는데 쓰이는 시각화 기법을 평가하는 것이다. 구체적으로 이 연구는 (1) 공학적 설계를 위한 시각화 기법의 비교 속성을 정하고, (2) 정해진 속성에 따라 시각화 기법을 비교하고 그 효율성을 연구한다. 공학 설계 과정에서 시각화 기법은 엔지니어와 공학적 정보 사이의 사용자 인터페이스이다. 엔지니어는 공학적 설계 중에 정보가 표현되는 방식에 따라 영향을 받는다. 특정 설계 과정에서 어떤 시각화 기법이 더 좋은지 알아보기 위한 사용자 실험이 진행되었다. 연구를 통해 특정 측면에서 두 시각화 기법의 차이를 찾을 수 있었다. 이 연구 절차가 공학적 설계에서 쓰이는 시각화 기법을 비교, 평가하는데 응용될 수 있을 것이라 기대된다. 또한, 향후 연구에서 심미성, 데이터 사용성, 그리고 도메인 지식에 대해서 다룰 수 있을 것이다.

주요어: Information Visualization, Comparative Evaluation, Engineering Design, Engineering Change, Data Envelopment Analysis

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