

**DESIGN AS A SEARCH PROBLEM: INTERACTIVE
VISUALIZATION FOR SYSTEM DESIGN UNDER UNCERTAINTY**

by
Michael Dale Curry

M.B.A. Business Administration – Georgia Institute of Technology, 2012
M.S. Aerospace Engineering – Georgia Institute of Technology, 2004
B.S. Mechanical Engineering – University of Kentucky, 2001

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Signature of Author..... **Signature redacted**
Department of Aeronautics and Astronautics
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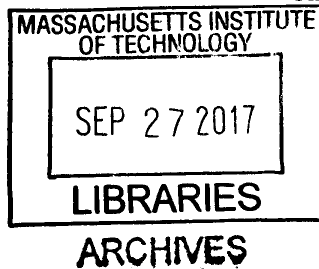
Certified by..... **Signature redacted**
Daniel E. Hastings
Cecil and Ida Green Education Professor of Aeronautics and Astronautics
Thesis Chair

Certified by..... **Signature redacted**
Adam M. Ross
Lead Research Scientist, Systems Engineering Advancement Research Initiative
Thesis Committee Member

Certified by..... **Signature redacted**
Remco Chang
Associate Professor, Computer Science, Tufts University
Thesis Committee Member

Certified by..... **Signature redacted**
Olivier de Weck
Professor of Aeronautics and Astronautics
Thesis Committee Member

Accepted by..... **Signature redacted**
Youssef M. Marzouk
Associate Professor of Aeronautics and Astronautics
Chair, Graduate Program Committee



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Michael Dale Curry

Abstract

In 2011, the Office of the Secretary of Defense (OSD) identified the need for improved methods of performing early conceptual trade studies and lifecycle analysis to design systems effective in a wide range of situations and adaptable to many others. This surge in interest within the DoD has been driven by a recognition that as systems grow in scale and complexity, and consequently cost, traditional methods of addressing design and operational uncertainties will no longer suffice. These challenges, which are not unique to the DoD, can be more broadly characterized as the need to achieve sustained value delivery from systems despite perturbations in design, context or stakeholder needs.

Epoch Era Analysis (EEA) was developed to better model problems with lifecycle uncertainties and has demonstrated its usefulness in prior research studies, but it still faces significant challenges to practical application. Specifically, EEA can result in large, multivariate datasets that are difficult to generate, visualize and perform analysis on. When performing exploratory analysis on such model-generated data sets, human interaction is often necessary to identify important subsets of the data, resolve ambiguity or find inconsistencies. Although prior research towards methods for applying EEA constructs has been performed, a prescriptive framework that explicitly considers human interaction does not exist. To make informed decisions, and design successful strategies for value sustainment, effective visualization and analysis techniques are needed to derive valuable insights from this data. These challenges motivate this thesis research.

The aim of this thesis is to leverage recent research in visual analytics and advanced systems engineering methods to develop a rigorous framework, with associated methods, processes, metrics and prototype applications that will result in new capabilities that better enable analysis and decision-making for long-run value sustainment. Several research contributions are outcomes of this thesis. First, the Interactive Epoch Era Analysis (IEEA) framework is introduced as a methodology for analyzing lifecycle uncertainty when designing systems to achieve sustained value delivery. IEEA provides a coherent theoretical framework to guide the development of human-usable analytic tools for early-stage system concept selection. Next, new interactive visualization applications for system concept selection are introduced to demonstrate the feasibility, usefulness and scalability of IEEA as an integrated visual analytics system. Finally, to characterize the benefits of interactive visualization applications for engineering design problems, the results of a controlled human-subjects experiment are presented.

Thesis Chair: Daniel E. Hastings

Title: Cecil and Ida Green Education Professor of Aeronautics and Astronautics and Engineering Systems

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List of Acronyms

AJAX	Asynchronous JavaScript and XML
ARI	Available rank improvement
BI	Business intelligence
COI	Community of Interest
CSS	Cascading Style Sheets
CSV	Comma-separated variables
D3	Data-driven documents
DoD	Department of Defense
DOM	Document object model
EEA	Epoch Era Analysis
eFNPT	Effective Fuzzy Normalized Pareto Trace
eFPN	Effective Fuzzy Pareto Number
ERS	Engineered Resilient Systems
FACT	Framework for Assessing Cost and Technology
FAFO	Fully accessible filtered outdegree
fNPT	Fuzzy Normalized Pareto Trace
FOD	Filtered outdegree
FPN	Fuzzy Pareto Number
FPS	Fuzzy Pareto Shift
HCI	Human Computer Interaction
HTML	HyperText Markup Language
IEEA	Interactive Epoch Era Analysis
IMR	Inspection maintenance and repair
JSON	Javascript object notation
MATE	Multi-Attribute Tradespace Exploration
MAE	Multi-Attribute Expense
MAU	Multi-Attribute Utility
MAUT	Multi-Attribute Utility Theory
MCSC	Marine Corps Systems Command
MDO	Multidisciplinary optimization
MIT	Massachusetts Institute of Technology
MOI	Metric of interest
NASA	National Aeronautics and Space Administration
NPT	Normalized Pareto Trace
NPV	Net-Present Value
OCV	Offshore construction vessels
OLAP	Online Analytical Processing
OSD	Office of the Secretary of Defense
PSV	Platform supply vessels
SAU	Single Attribute Utility
S&T	Science and technology
SEARI	Systems Engineering Advancement Research Initiative
TSE	Tradespace exploration

UX	User Experience
VASC	Valuation Approach for Strategic Changeability
VWFO	Value-weighted filtered outdegree
XML	eXtensible Markup Language

1.0 Introduction

1.1 Motivation

In April 2011, the Office of the Secretary of Defense (OSD) identified the development of engineered resilient systems (ERS) as a science and technology (S&T) strategic investment priority. Their use of the term “resilient” causes some semantic confusion, but a close examination of the problems they describe reveals an interest in improving how early conceptual trade studies (pre-Phase A) and system lifecycle analysis are performed when there is uncertainty in future stakeholder needs, operating environment or changes in the system over time. The surge in interest within the DoD has been driven by a recognition that as systems grow in scale and complexity, and consequently cost, traditional methods of addressing these uncertainties will no longer suffice. Recent publications out of the ERS community of interest (COI) have provided prospective on the DoD’s needs as well as attempted to identify gaps in current system design and acquisition approaches [1,2,3]. Several researchers and practitioners have also begun to investigate how to define this problem and develop new methods, techniques and tools to assist designers in early-phase system concept selection activities. The ultimate goal of this strategic initiative can be more broadly characterized as the need to achieve sustained value delivery from systems in spite of changes in design, context or needs.

The objectives of the ERS program and many of the issues due to uncertainty about the future they describe are not unique to the DoD. Similar issues often arise in the design of space systems, commercial products and in infrastructure development. Many systems engineering practitioners view design processes, like the systems engineering “V” or the phased design process described by the NASA Systems Engineering Handbook [4], as a blueprint to be followed that will result in systems capable of satisfying the needs of stakeholders throughout the lifecycle of that system. This type of approach can be problematic, however, especially when there is uncertainty about the future or when the nature of what system stakeholders perceive as valuable over time is not well articulated or understood. In such situations the design process might best be viewed as exploratory where processes lead to unexpected results that require a decision-maker or analyst to iterate back through previous processes to comprehend a problem and reach a conclusion. The iterative nature of the design process, often characterized by successful knowledge discovery only after it is preceded by trial and error and intermediate failure, has been referred to as “**design as a search problem**” [5].

Epoch Era Analysis (EEA) and related approaches have been developed to better model problems with lifecycle uncertainties and have demonstrated their usefulness in prior research studies, but they still face significant challenges to practical application for informing decision-making in problems like those now posed by the DoD. Specifically, EEA can result in large, multivariate datasets that are difficult to generate, visualize and perform analysis on. The analysis of the model-generated data sets associated with EEA

studies can be challenging not only because of the size of the data set in terms of number of records and dimensions, but also due to issues related to the interpretation of results. Models of system performance or stakeholder value may contain embedded assumptions or errors that lead to confusing or misleading output data. Even when there are no concerns with the underlying models that generate the data there can still be ambiguity about what constitutes desirable characteristics and behaviors of the system designs that are being modeled. When performing exploratory analysis on such model-generated data sets, human interaction is often necessary to identify important subsets of the data, resolve ambiguity and recognize patterns or inconsistencies. However, although prior research towards methods for applying EEA constructs has been performed, a prescriptive framework that explicitly considers human interaction does not exist. To make informed decisions and design successful strategies for value sustainment, effective visualization and analysis techniques that consider human interaction are needed to derive valuable insights from this data

Design tools for assisting analysts and decision-makers discover insights while engaged in these types of system design problems under uncertainty should also reflect the exploratory nature of the problem. Think of them as part of a collaborative process between a human and a computer, where each has its own distinct advantages [6,7]. Exponential improvements in processing power and data visualization capabilities in recent years encourage us to reexamine our approaches to balancing computer automation with human intuition in systems engineering decision-making. Ongoing research and applications from visual analytics are often focused on similar types of problems. Visual analytics tools have been developed and have shown promise in application areas such as healthcare, finance and combating global terrorism [8,9,10]. These areas have some similarities with system design problems in that they must consider a wide range of possible outcomes, deal with large amounts of data, and the nature of “success” isn’t always clearly defined or agreed upon.

This thesis examines how incorporation of research from the field visual analytics can facilitate the development of a generalizable, prescriptive framework that can be leveraged to develop interactive design tools and overcome the challenges described. As described by Thomas and Cook, visual analytics is “the science of analytical reasoning facilitated by interactive visual interfaces.” [11]. It can attack certain problems whose size, complexity, and need for closely coupled human and machine analysis may make them otherwise intractable [12]. It is argued in this thesis that system design problems with uncertainty often fit this description. While much of this thesis is dedicated to the discussion of principles from the field of visual analytics and issues related to interactive visualization, it is primarily focused on making a contribution in the area of research dealing with the design of complex engineering systems under uncertainty. Where practical, this thesis also considers how these integrated visualization and analysis environments can best be merged with existing systems engineering practices.

1.2 Problem Statement and Research Questions

Prior research has provided some background on ways EEA can be applied to model the impacts of various perturbations¹ on system value. However, to fully address the challenges described in the previous section a more comprehensive framework for the analysis of system value sustainment that explicitly considers human interaction is necessary. This leads to the aim of the research presented here. This thesis should contribute to the engineering literature a new prescriptive framework that augments traditional EEA approaches with detailed processes, descriptive quantitative metrics, analytic methods, and interactive visualization techniques. It is hypothesized that this framework will fundamentally enable new capabilities and insights to be derived from EEA, resulting in superior dynamic strategies for sustaining system value.

As discussed previously, the top-level question that this thesis examines is, “How can we better enable decision makers to design complex systems that deliver sustained value to stakeholders in a wide range of operations and multiple alternative futures?” Based on this question, the primary hypothesis of this thesis is that incorporating research from the field of visual analytics to extend EEA can help us better address the challenges to practical application for the types of problems described by the engineered resilient systems (ERS) community of interest (COI). That primary hypothesis can be separated into three lower-level objectives that are motivated by the problem statement and EEA related challenges described in the preceding section. These objectives tie directly to the following three research questions:

1. **(RQ1)** How can the value sustainment of complex systems be enabled through an early-phase design framework that incorporates EEA and explicitly considers human interaction?
2. **(RQ2)** How can existing techniques from the field of visual analytics be incorporated into EEA to enable analysis and comprehension of driving factors of sustainable system value in dynamic operating environments?
3. **(RQ3)** Does interactive visualization improve design problem decision-making and, if so, what are the relative contributions of representation, interaction or other factors to user performance?

The research methodology for answering these research questions is detailed in the next section of this chapter. Several contributions are anticipated as outcomes from the research effort associated with addressing these three research questions. First, this thesis contributes the results of a controlled human-subjects experiment that decouples the relative contributions to human performance of interaction, visualization and individual differences in subjects when they analyze design problems using interactive visualization tools. Next, the Interactive Epoch-Era Analysis (IEEA) framework, comprised of 10 processes grouped in 6 modules, is introduced as a means for analyzing lifecycle uncertainty when designing systems to achieve sustained value delivery. Finally, to enable new capabilities and improve the analysis of value sustainment as a

¹ Beesemyer categorized perturbations as being either disturbances or shifts [15]. Disturbances have a short-duration impact and shifts have a long-duration or permanent impact on design, context, or needs.

dynamic, continuous, and path-dependent property of candidate systems, new interactive visualizations for both epoch and era analyses are introduced. It is hypothesized that the extension of interactive visualization to system design problems with lifecycle uncertainty will result in improved comprehension of the nature of underlying trades and improve a designer's ability to communicate their decision-making rationale.

1.3 Methodology

While the primary objective of this research is to determine how to better inform decision-making in the design process, ultimately resulting in systems with sustained value delivery, this thesis aims to make contributions to topics supporting the broader research agenda. Specifically, this thesis seeks to develop a prescriptive design framework with new metrics, algorithmic methods and interactive applications to facilitate improved analysis and comprehension by decision-makers. To that end, the six-phase research methodology shown in Figure 1-1, inspired by prior research studies by Richards [13] and Corbin [14], will be applied. The methodology includes the following phases:

1. Knowledge capture and synthesis
2. Framework, method and metric development
3. Prototype interactive visualization development
4. Review by subject matter experts
5. Controlled human subjects experiment
6. Case study applications.

Each phase should not be regarded as a discrete activity in a serial process but rather one aspect of an iterative, concurrent process of continuous learning, revisiting of assumptions, and development and testing of hypotheses. Combined, these six phases serve as a concrete validation plan for the working hypotheses of this thesis and provide a means of answering the three primary research question described in this chapter.

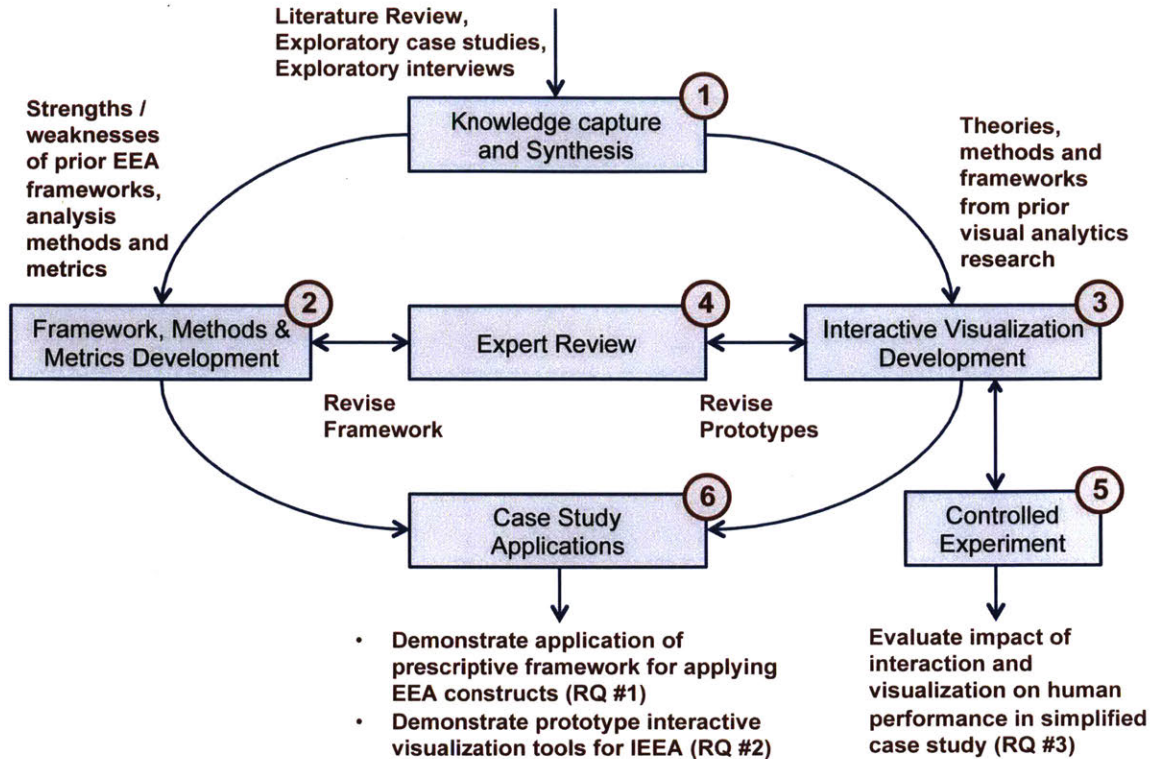


Figure 1-1: Six-phase Research Approach

The first phase in the proposed research approach is to conduct a thorough literature review to capture knowledge in a variety of fields, including prior research in advanced system engineering methods such as EEA and recent research in the areas of visual analytics and interactive data visualization that may be applicable to the current research. Exploratory interviews are also conducted with subject matter experts (SME), senior systems engineers and key stakeholders in various candidate application case studies. The goal of this phase is to identify strengths and weaknesses of existing design frameworks, methods, metrics and analysis tools in the context of the types of challenges motivating this research. This phase should also identify theories, models, frameworks and enabling techniques from the field of visual analytics that can be incorporated to overcome challenges or enable new capabilities.

During the second phase of this research, which focuses on framework, method and metric development, gaps in the existing approaches are examined, and modifications and additions are made to fill these gaps. The intended output of this phase is a new prescriptive framework for applying EEA constructs to generate, evaluate and decide among design alternatives given future uncertainty. Exploratory case study examples, some from research reviewed in the previous phase, are used to test the proposed framework, algorithms and metrics for internal validity before implementing them in prototype interactive applications. Informal expert reviews of the framework will also be used to iterate and update the individual processes.

The third phase, which occurs concurrently with the second phase, will incorporate enabling research from the field of visual analytics, identified in the first phase, to implement and test the proposed IEEA framework. Elements from the key steps in the visual analytics process (visual mapping, model-based analysis, and user interactions) are mapped to prototype applications that implement the process phases of the IEEA framework. Prototype interactive visualizations will also be assessed using qualitative measures of effectiveness in the fourth phase of this research.

The fourth phase, which occurs concurrently with the second and third phase, incorporates the opinions of subject matter experts (SME's) on both the proposed IEEA framework and the prototype interactive visualizations that implement it through informal interviews and expert review. Qualitative measures of effectiveness will be assessed using the same exploratory case studies used in the second phase. Feedback from SME's on comprehension and usability of the framework and interactive visualizations will be used to iterate and revise both the framework and prototypes.

The fifth phase, which occurs concurrently with the third phase, implements a controlled human subjects experiment. The experiment aims to decouple and evaluate the impact of interaction and visualization on human performance by measuring performance differences between four treatment groups corresponding to different analysis tools. These analysis tools are each implemented using similar interaction and visualization types as those used to implement the IEEA framework prototypes. The experiment measures interpretation errors, number of achieved benchmark goals and task completion time of subjects analyzing a simplified multi-epoch car design problem, which in turn assesses quantitative measures of visualization effectiveness.

The sixth and final phase in this research focuses on demonstrating the prescriptive value of the new IEEA framework and corresponding metrics, algorithmic methods and visualizations. External validity of IEEA is assessed through case studies using parametric modeling and simulation to assess candidate system architectures in separate case studies: (1) A multi-mission on-orbit service vehicle; and (2) A commercial ship design application. The first case study provides a detailed assessment of each of the IEEA process steps and the second case study demonstrates the scalability of the framework and prototype applications to a larger data set.

1.4 Thesis Outline

The remainder of this thesis is structured as follows:

- In Chapter 2 an overview of past literature relevant to this research effort will be discussed. Specifically, prior work in the areas of visual analytics and advanced systems engineering methods will be discussed in detail.
- Chapter 3 discusses the considerations associated with development and application of visual analytics tools. The new capabilities they provide and how

these can be leveraged to improve to the discovery of insights in system design problems are also presented.

- Chapter 4 will provide a detailed discussion of IEEA, the proposed prescriptive framework for evaluating design alternatives given future uncertainty. Interactive visualization applications that implement the relevant process steps will be presented.
- Chapter 5 describes the controlled human subjects experiment developed to decouple the relative contributions to human performance of interaction and visualization when subjects analyze a simplified design problem using interactive visualization tools. Overview of the experimental protocol, treatment groups and results will be discussed.
- Chapters 6 and 7 provide case studies to demonstrate how descriptive information is produced, analyzed, and visualized to compare design, change option and strategy combinations. The first case study walks through the new IEEA framework in detail using a case study for the design of an on-orbit servicing vehicle (space tug). The second case study, which focuses on the design of commercial ships, demonstrates scalability of visualization and analysis techniques on a larger scale problem and extensibility to a different problem domain.
- Finally, Chapter 8 will provide discussion and some concluding remarks about the contributions of this research to the broader field of systems engineering. Candidate topics for future research are also discussed.

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2.0 Literature Review

The ultimate goal of this research is to provide designers with a comprehensive approach for evaluating system value sustainment to inform improved decision making in the early conceptual phase of the system lifecycle. Specifically, this research explores the coupling of techniques from visual analytics to demonstrate how an integrated visualization and analysis environment for making sense of high-dimensional EEA data can lead to new capabilities and improved insights. This is a multi-faceted research topic and as such draws on several areas of previous research. The four main areas of literature reviewed are:

- DoD S&T efforts under the ERS initiative and related prior research that define the meaning of value sustainment as used in the current research.
- Advanced systems engineering methods research including epoch-era analysis.
- Visual analytics and related research on interactive visual interfaces.
- State of the practice systems engineering applications, workflows, processes and tools.

Although there is some overlap between these areas, they are largely distinct from one another both in their aims and in the researchers and practitioners involved in their study. Each will be described in further detail in the following subsections.

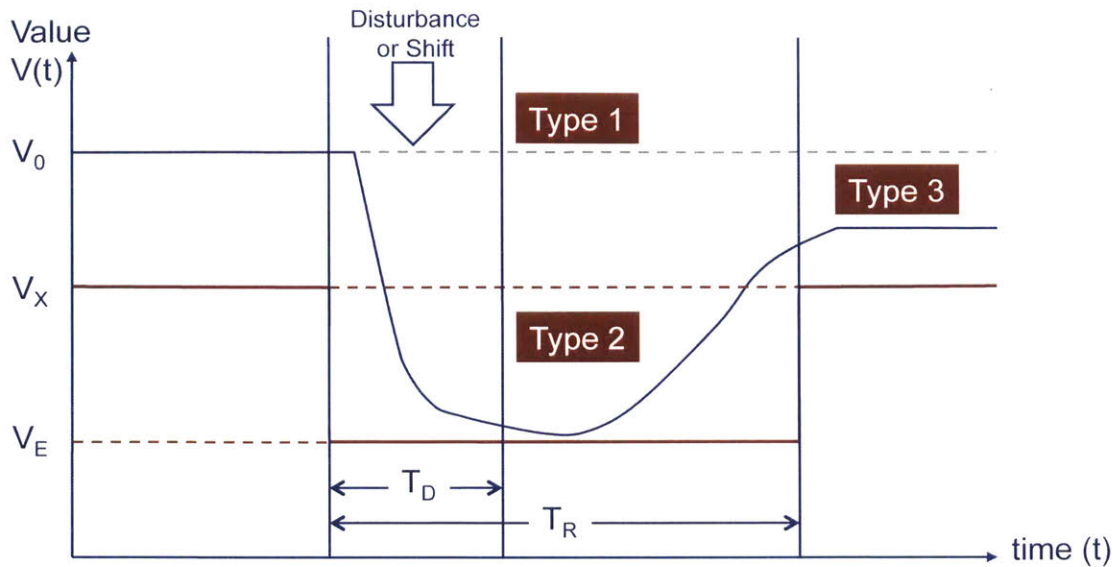
2.1 ERS / System Value Sustainment

The challenges described by the ERS community of interest (COI) within the DoD served as the initial motivation for this research [1,2,3]. As previously noted, however, their use of the term “resilient” causes some semantic confusion since the desired system behavior they describe is similar to the concepts described in prior literature as survivability, changeability, value robustness or value sustainment. It is therefore important to review the various definitions used by the ERS COI and other authors to clarify the goals of this thesis.

A significant prior body of work exists that describes what it means for a system to be resilient, survivable, value robust or other notions related to the concept of value sustainment over time, but the precise definition is not universally agreed upon. Among the first sources to use the phrase “resilience engineering” [15] described the failure of a system as being a result of its breakdown or malfunction due to its inability to adapt or cope with the complexities of the real world. The authors provide topologies of the meaning of resilience, but their focus is primarily system safety and risk management that is somewhat different than the focus of the current research effort described here. Later work by Richards [13,16], Jackson [17], Jackson and Madni [18], and Madni [19] focus on frameworks for architecting systems to avoid, survive and recover from disruptions. Each of these authors describes concepts similar to what is referred to in the current work as value sustainment. Jackson and Madni each describe a resilient system as one that has

“the ability to circumvent, survive, and recover from failures to ultimately achieve mission priorities even in the presence of environmental uncertainty” [19]. Richards described principles for system architecting for survivability, but his definition for survivability is similar to Jackson and Madni’s definition of resilience. Adding to the semantic confusion, follow-on work by Beesemyer [20] that leveraged the work of Richards referred to a similar concept as value sustainment. The definition used by Richards for survivable systems is “the ability of a system to minimize the impact of a finite duration disturbance on value delivery, achieved through either (1) the reduction of the likelihood or magnitude of a disturbance; (2) the satisfaction of a minimally acceptable level of value delivery during and after a finite disturbance or; (3) timely recovery from a disturbance event” [16]. Richards also proposed a means for quantifying changes in system value due to disruption using two temporally based metrics: time-weighted average utility loss and threshold availability. What is common to most of the definitions suggested is an acknowledgement that complex systems must be designed to continue to deliver sustained value to their stakeholders even if uncertainty exists about the way a system will be required to operate in the future.

This thesis adopts the definition of the generalized concept of value sustainment, as given by Beesemyer, to be “the ability to maintain value delivery in spite of epoch shifts or disturbances.” Figure 2-1 and Figure 2-2 below summarize this concept and reflect how notions of value sustainment will be considered in this research effort. In these figures, the nominal value delivered by a system is (potentially) impacted by a perturbation (characterized as either a disturbance or a shift). A disturbance is a short duration event, likely to revert imposed change on the design, context, or needs for a system, while a shift is a long duration event, unlikely to revert imposed change on the design, context, or needs for a system. A system that exhibits the desired behavior is one that is either not impacted, or maintains value above the indicated threshold, and restores that value delivery to a higher acceptable level after a threshold period of time.



Value sustainment - Ability of a system to maintain value despite an epoch disturbance or shift through:

Type 1: the reduction of the likelihood or magnitude of a disturbance

Type 2: the satisfaction of a minimally acceptable level of value delivery during and after a disturbance

Type 3: maximization of the recovery of value-delivery within a permitted recovery time

$V(t)$ = value over time
 V_0 = original value prior to disturbance/shift
 V_E = minimal acceptable value
 V_X = required value threshold
 T_D = Disturbance duration
 T_R = permitted recovery time

Figure 2-1: Graphical representation of short run impacts of perturbations on value delivery[13,20].

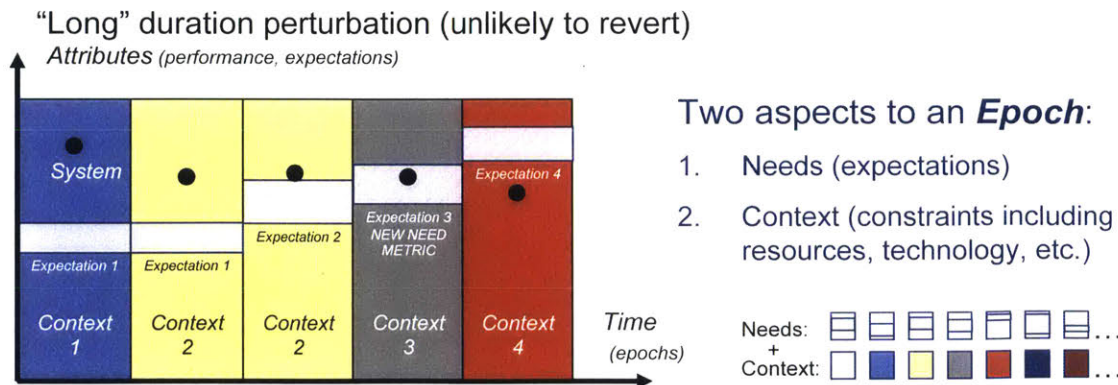


Figure 2-2: Graphical representation of long run impacts of perturbation on value delivery

In addition to efforts to define the desired system behavior over time, much of the early work of the ERS community has focused on identifying gaps in existing applications and techniques for tradespace exploration [21]. A significant gap in most existing tradespace exploration applications is that they only evaluate system alternatives for a static set of stakeholder needs, operating context (e.g. mission) and system state at initial deployment. This effectively ignores system properties that only manifest themselves with changes over time, the so called “ilities” (e.g. reliability, adaptability, etc.). This status quo is not surprising since setting static performance requirements that define the system design are central to the system acquisition processes used by both the DoD and NASA. Additional details on research related to systems engineering applications will be provided in Section 2.4.

2.2 Advanced Systems Engineering Methods

The second area of background research explored as part of the current effort is prior advanced methods that can be applied in early-phase conceptual design of systems. Though exploration of the space of possible designs is not a new concept, some recently developed methods have potential to fill the previously discussed gaps in applications and methods needed by the DoD.

2.2.1 Multi-Attribute Tradespace Exploration and Epoch-Era Analysis

Conceptual design methods for identifying system trades and optimizing the system under design for certain performance attributes have been a focus of research for some time [22,23]. More recently researchers have coupled design space exploration with multi-attribute utility theory (MAUT) [24] where system utility, which is computed as a function of system performance attributes, is used as a surrogate for value. This is useful for non-commercial systems where it is difficult to monetize value delivery through metrics such as net present value (NPV). Research in this area has given rise to methods like multi-attribute tradespace exploration (MATE) [25,26]. MATE is a conceptual design method that compares large numbers of candidate system designs using experimental designs to enumerate vectors of design variables that are evaluated by system performance models. The performance attributes for each design are then evaluated using a valuation metric, typically a multi-attribute utility (MAU) function, and plotted against their respective costs in a cost versus utility (as benefit) scatter plot to visualize the tradespace as shown in Figure 2-3. Often the goal of this activity is to identify the frontier of Pareto optimal solutions. Comparing alternatives in this way helps mitigate potential biases or premature fixation on a single-point design. While MATE is a useful approach it still does not directly address future uncertainties of the nature that are the focus of the current research.

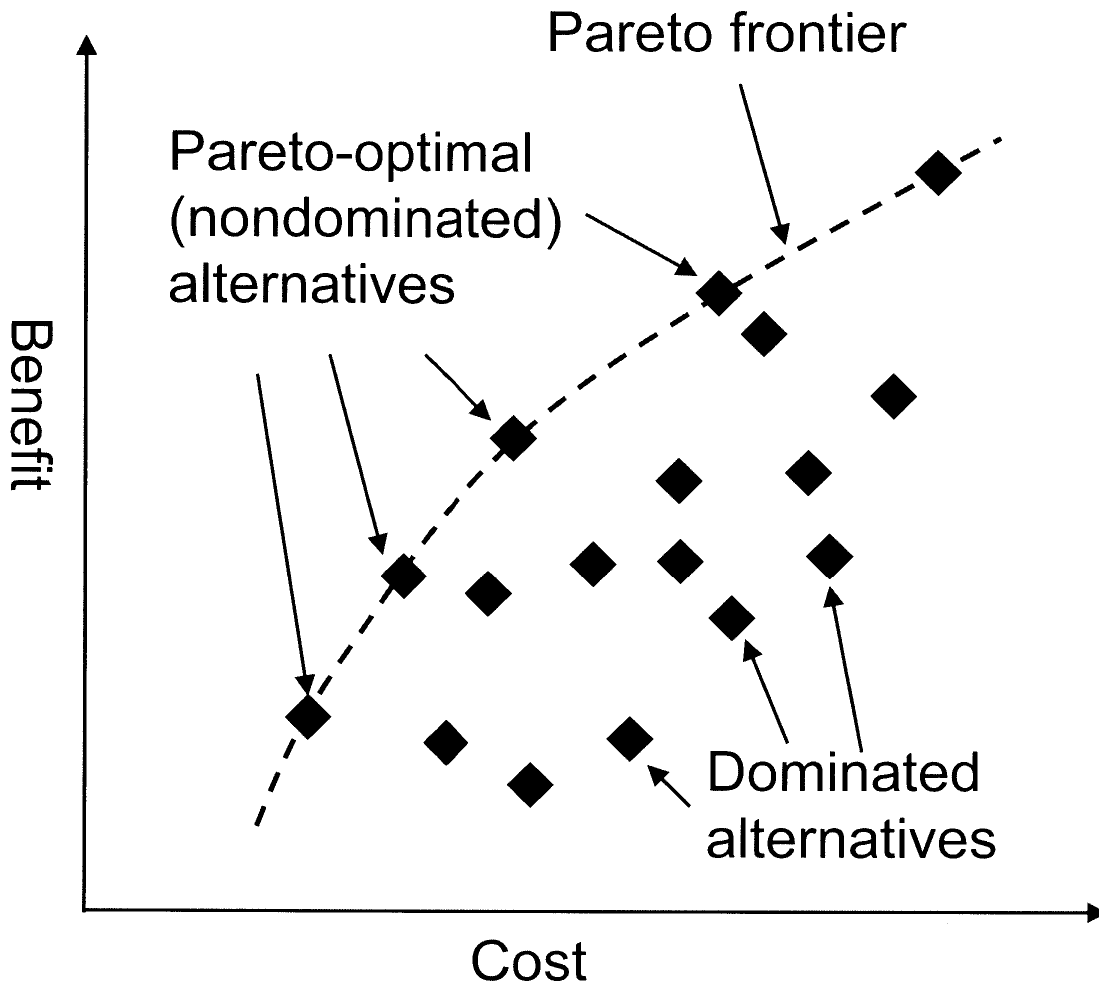


Figure 2-3: Notional tradespace of cost versus benefit (e.g. value, utility)

To extend the capabilities of MATE, Ross [27] described a new method called Epoch-Era Analysis (EEA) that is useful for framing problems with uncertainties in stakeholder needs and context. EEA is designed to clarify the effects of changing contexts over time on the perceived value of a system in a structured way [27,28]. The base unit of time in EEA is the epoch, which is defined as a time period of fixed needs and context in which the system exists. Epochs are represented using a set of epoch variables, which can take on continuous or discrete values. These variables can be used to represent any exogenous uncertainty that might have an effect on the usage and perceived value of the system. Weather conditions, political scenarios, financial situations and the availability of other technologies are all potential epoch variables. Appropriate epoch variables for an analysis include key (i.e., impactful) exogenous uncertainty factors that will affect the perceived success of the system. A large set of epochs, differentiated using different enumerated levels of these variables, can then be assembled into eras, ordered sequences of duration-labeled epochs creating a description of a potential progression of contexts and needs over time as shown in Figure 2-4. This

approach provides an intuitive basis upon which to perform analysis of value delivery over time for systems under the effects of changing circumstances and operating conditions, an important step to take when evaluating large-scale engineering systems with long lifecycles.

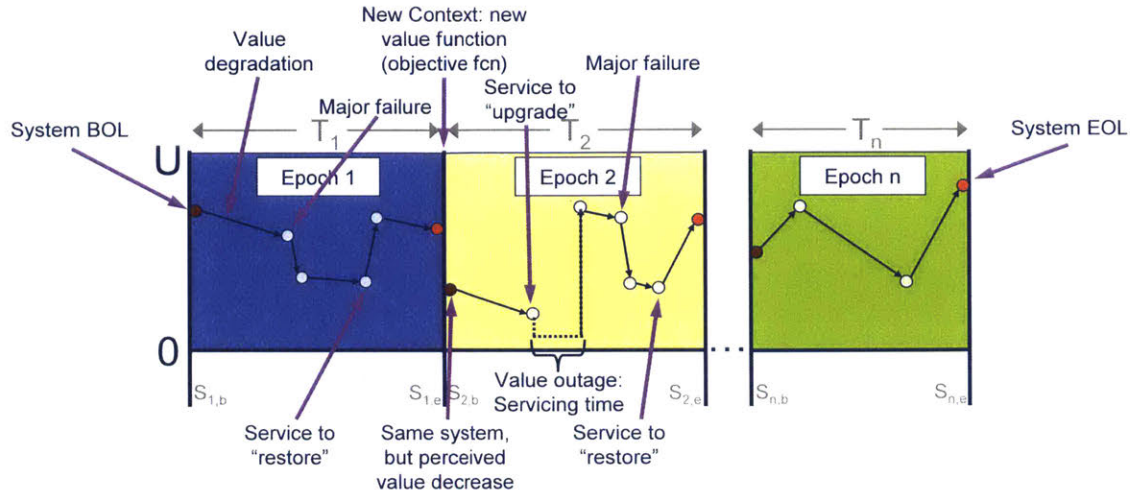


Figure 2-4: Notional example of value over time for a serviceable system [28]

Encapsulating potential short run uncertainty (i.e., what epoch will my system experience next?) and long run uncertainty (i.e. what potential sequences of epochs, or eras, will my system experience in the future?) allows analysts and decision makers to develop dynamic strategies that can enable system value sustainment. Key challenges in application of EEA up to this point involve eliciting a potentially large number of relevant epochs and eras, conducting analysis across these epochs and eras, and extracting useful and actionable information from the analyses. Schaffner [29] showed that the number of potential eras to consider could grow very quickly, becoming computationally infeasible. As an example, an epoch space represented by 5 epoch variables, each with 3 levels, would result in $3^5 = 243$ possible epochs. If the length of our eras is 10 epochs and each epoch can transition between any other epoch then the size of the potential era space would be $243^{10} \sim 10^{24}$ eras. This means that for many problem formulations it is not feasible to evaluate systems across all or even a large fraction of potential eras.

2.2.2 Metrics for Value Sustainment through Changeability

Several research efforts since Ross' original work have developed EEA further to consider changeability options and path dependencies between epochs. The valuation approach for strategic changeability (VASC) was proposed by Fitzgerald to generate quantitative descriptive information regarding the value of included system change options, without resorting to many of the assumptions implicit in real options analysis and other financial options method [30,31,32]. VASC introduces several metrics that can be used to characterize the behavior of systems with change options during multi-epoch

analysis. The metrics included Fuzzy Pareto Number (FPN), effective Fuzzy Pareto Number (eFPN), effective Normalized Pareto Trace (eNPT), Fuzzy Pareto Shift (FPS), and Available Rank Improvement (ARI). VASC also proposed the concept of defining epoch-level strategies (e.g. survive, maximize utility or efficiency) that define how a system will use change options when it encounters and epoch shift. Doing so allowed the consideration of how design-strategy pairs impacted the evaluation of designs across epochs.

Another useful metric for quantifying valuable changeability proposed by Ross [27] is Filtered Outdegree (FOD), which represents the number of change paths out of a design to various target designs given a set of filtering constraints on resource usage such as execution time and expense (e.g. cost). Since FOD only captures the number of change paths, not necessarily whether they are valuable or useful, several follow-on works attempted to define metrics for various versions of Value-Weighted Filtered Outdegree (VWFO) [33,34,35] to assess the utility gain that could be achieved through execution of various change options. Original versions of this metric relied on weighted averages of potential utility gains across available transition paths. Since MAU functions may not be the same across different epochs this metric may not be appropriate when comparing designs between epochs. Later versions of VWFO used path-counting methods that only counted outward change paths that resulted in a positive gain in utility, but this metric also has similar shortcomings.

Focusing more on long run strategies, Schaffner [29] provides a convincing argument that FOD may be a more appropriate metric than any of the proposed VWFO metrics since in many cases it may be beneficial to execute a change to affect a short-term loss of utility in order to achieve a longer-term net gain. Schaffner further notes that most past applications of FOD have focused on single arc change paths to determine the number of target end states that an original design can achieve via execution of a change mechanism. His proposed metric for Fully Accessible Filtered Outdegree (FAFO), which also captures additional end states that can be reached through multiple change mechanisms, is adopted for the research presented here on IEAA. A potential drawback to IEAA, which was discussed in some detail by Schaffner [35], is the computational complexity that arises as more and more design alternatives, epochs and eras are evaluated which can make the decision problem intractable. Approaches for overcoming this deficiency are also considered as part of the research described in this thesis.

2.2.3 Graph Theory and Network Analysis Metrics and Analysis Methods

Several recent theses on IEAA-related research have identified improved network analysis techniques applied to analysis of changeability as a candidate for future work [29,30,36]. This and other prior research on graph theory applied to design [37,38] has demonstrated that many more levels of analysis and understanding may be possible with epoch networks when evaluating changeability. First, as discussed in the proceeding section, metrics for identifying valuable changeability have historically focused on the number of change paths available to a design rather than on characterization of centrality within the network. Centrality metrics are frequently applied in other fields to analyze

social networks, supply chains and epidemiological studies on the spread of disease to identify the most “important” nodes within a graph. Importance may be thought of either as a related to the type of flow through the network [39] or a measure of the of a nodes involvement in the cohesiveness of the network [40]. As shown in Figure 2-5, depending on the centrality metric applied the nodes that are considered most important may be different. Metrics for closeness could be used to identify designs that are more proximate to other designs in terms of change cost, time or another resource. Other metrics may have the potential for identifying epochs that exhibit a high level of betweenness, connecting otherwise disparate futures [29,41]. When examining the all the shortest paths between nodes in a network betweenness centrality quantifies how frequently a particular node is in the path between other nodes. If nodes represent designs in a tradespace network, a node with a high degree of betweenness may represent a design that can more easily be changed into other reachable designs. Eigenvector centrality is central except that it assigns a relative importance to each node. More frequently used in past EEA research is degree centrality (typically outdegree) which measures only the number of connections to a node, not necessarily their relative importance. Katz centrality is a generalization of degree centrality and harmonic centrality is closely related to closeness centrality.

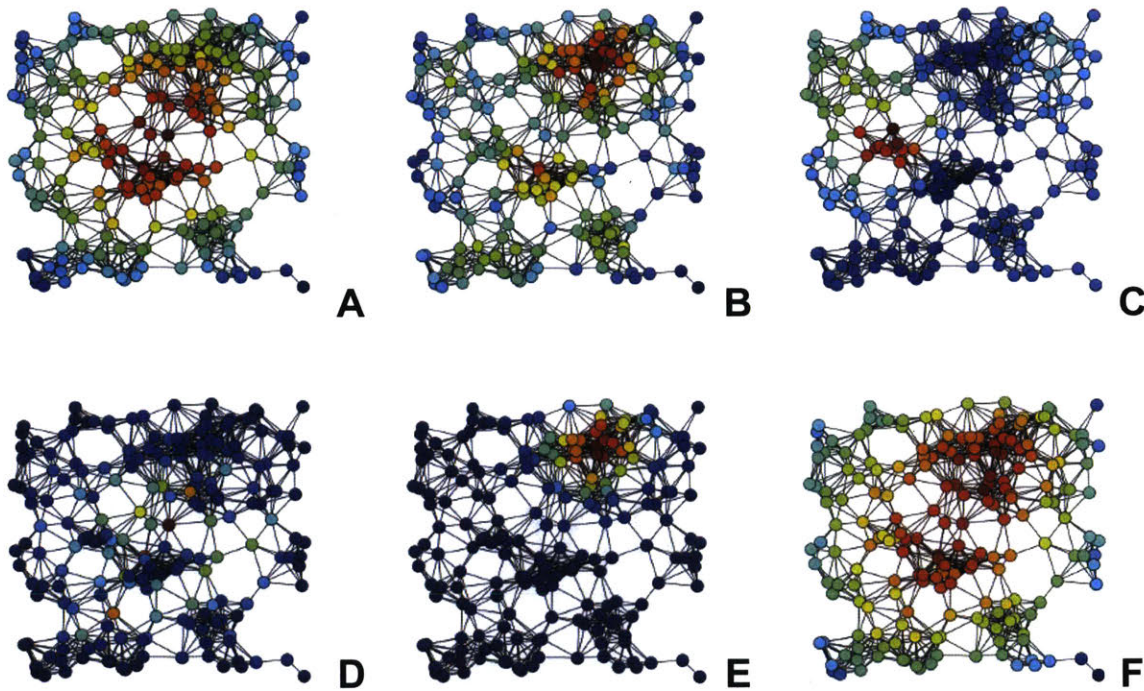


Figure 2-5: Examples of the same graph using color to encode the different centrality metrics: A) Closeness centrality, B) Degree centrality, C) Katz centrality, D) Betweenness centrality, E) Eigenvector centrality and F) Harmonic centrality [42].

In addition to centrality metrics there are also potential benefits of incorporating analytic methods from graph theory to enable new insights and capabilities for changeability analysis. Dijkstra’s algorithm, a path planning method designed to find

shortest paths between nodes in a network, can be used to efficiently compute the full accessibility matrix and thus FAFO [29,43]. Community detection algorithms like the Louvain Method have also shown potential benefits to the present research. The method is a greedy optimization method that can identify the best possible groupings of nodes within a network [44]. These groupings are referred to as “communities” in this thesis. When coupled with centrality metrics this method can help identify steady state “limit cycles” within communities that are a small subset of designs that are settled into as epochs change. These subsets of designs are related to the concept that Fitzgerald [30] referred to as design “families”. A potential benefit is that era analysis would no longer need to be used to compare lifecycles of initial design points, but rather the performance of the various design families. As shown in Figure 2-6, network visualization such as a force-directed graph can indicate the potential extent of such communities and families in a way that is more easily identifiable than the adjacency matrix representation used by Fitzgerald. Potential benefits of extending such visualizations to include interactivity will be discussed in Section 2.3

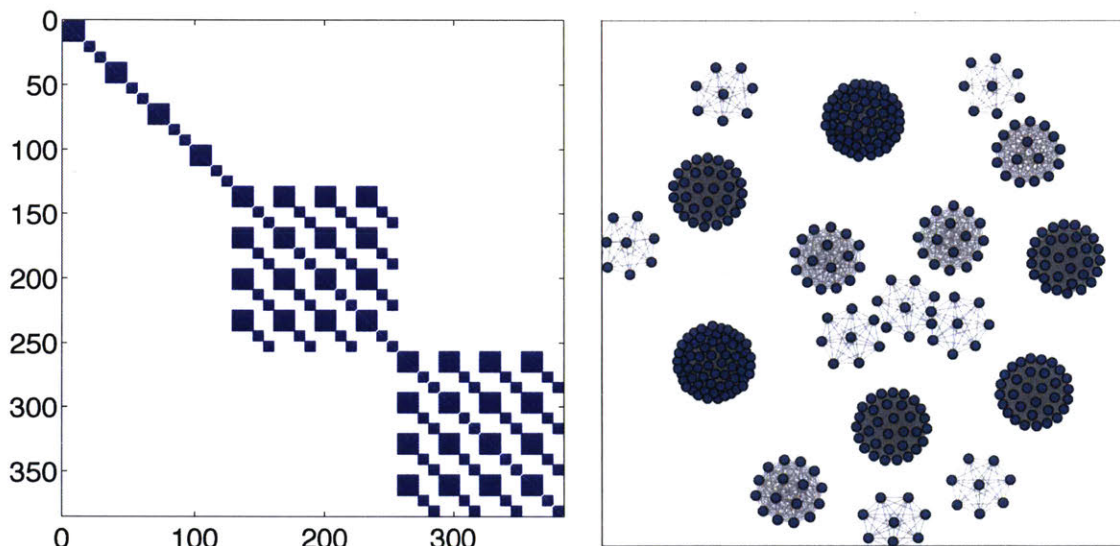


Figure 2-6: Comparison between full accessibility matrix representation using (left) adjacency matrix and (right) force-directed graph

2.2.4 Methods / Processes based upon Epoch-Era Analysis

In addition to constructs and metrics, some prior research has been performed to develop structured methods for operationalizing EEA that are relevant to this thesis. The Responsive Systems Comparison (RSC) method, proposed by Ross et al. [45,46] as a method for applying MATE and EEA, was developed to study system value sustainment through changeability. The purpose of RSC as described by Ross et al., is to “guide the...practitioner through the steps of determining how a system will deliver value, brainstorming solution concepts, identifying variances in contexts and needs (epochs)

that may alter the perceived value delivered by the system concepts, evaluating key system trade-offs across varying epochs (eras) to be encountered by the system, and lastly developing strategies for how a designer might develop and transition a particular system concept through and in response to these varying epochs”. An overview of the processes in the RSC method is shown in Figure 2-7.

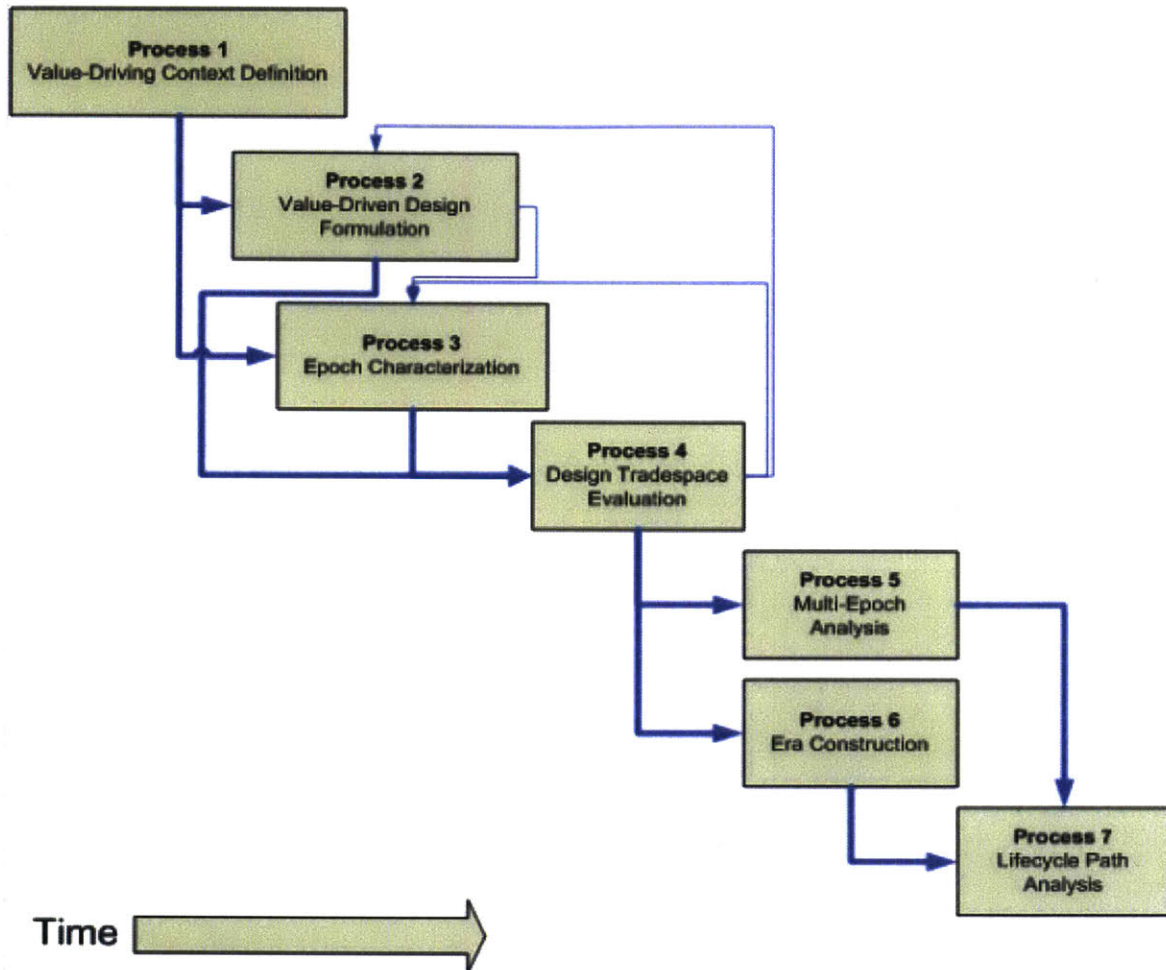


Figure 2-7: Overview of the Responsive Systems Comparison (RSC) method [45,46]

More recently, Schaffner [29] proposed the RSC-based Method for Affordable Concept Selection (RMACS) that expands the original seven processes of RSC to nine and focused on studying system affordability through application of multi-attribute expense (MAE) to more effectively capture all resources expenditures required to realize a given system. An overview of the RMACS processes is shown in Figure 2-8. Inspired by research in the field of visual analytics that will be described in the next section, IEEEA extends prior research on RCS and RMACS by explicitly considering the tight coupling of algorithmic and visual analysis through interaction.

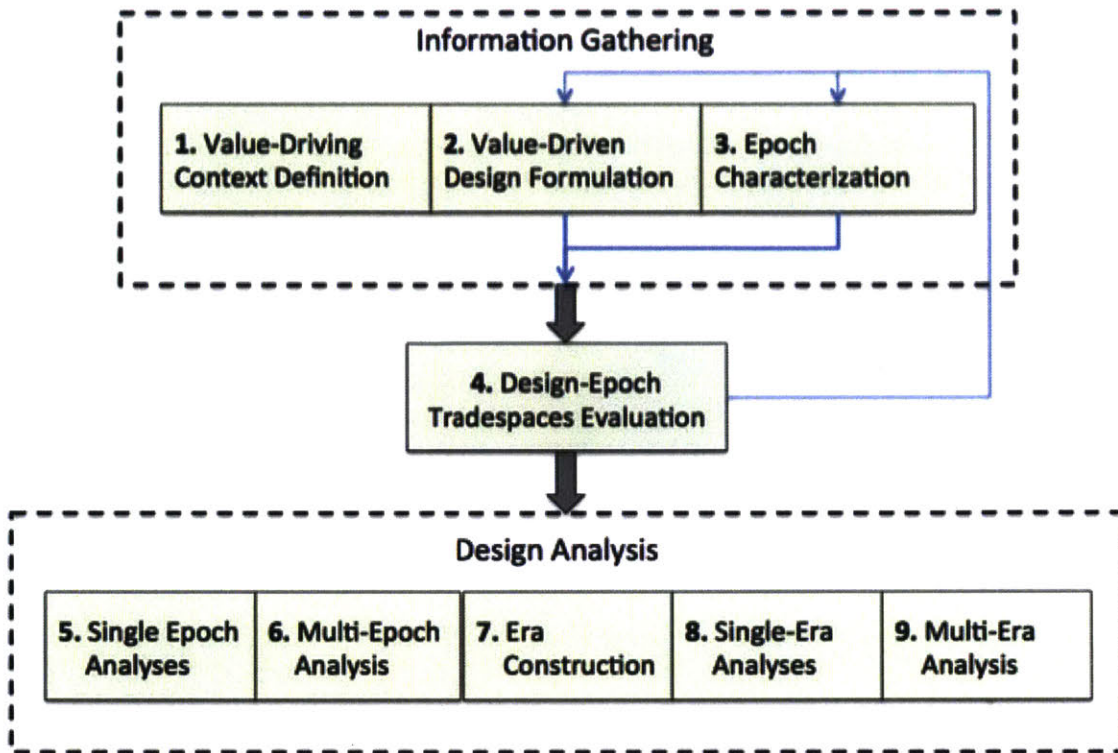


Figure 2-8: Overview of the Gather-Evaluate-Analyze structure of the RMACS method [29]

2.3 Visual Analytics and Interactive Visualization

Effective analysis of EEA generated data to derive valuable insights enables analysts to make informed decisions and design successful strategies for value sustainment. Techniques from visual analytics are key to IEEA and have been applied successfully in other domains to solve real-world problems. Visual analytics applications are beneficial for addressing problems whose size, complexity, and need for closely coupled human and machine analysis may make them otherwise intractable [12,47]. A recent example is the creation of a visual analytics application for detecting financial wire fraud [48,49]. In banking, the nature of fraud is ill-defined and constantly evolving, much like the nature of value among different decision makers in system design. A similar comparison can be made with recent visual analytics applications in the field of healthcare that must also frequently contend with ill-defined problems. The same data, explored by different medical professionals can lead to different decisions for a variety of reasons including risk aversion, available resources, or experience-level [50]. Additional examples can be found in such diverse domains as infrastructure maintenance [51] and understanding the nature of global terrorism [52]. Clearly many other large-scale problem have seen significant benefits by coupling the skills of subject matter experts with well-developed visual analytics applications that help them consider and comprehend complex data.

Visual analytics extends beyond traditional scientific visualization and focuses on extracting insights from data using interactive visual interfaces [53]. Interactive visualizations are used to integrate a user's knowledge and inference capability with numerical and algorithmic data analysis processes. Thomas and Cook presented the first widely accepted roadmap for visual analytics research in their seminal book [54]. As they described, the research agenda in this field seeks to develop "the science of analytical reasoning facilitated by interactive visual interfaces". Keim et al. updated the roadmap and provided the following revised definition of visual analytics: "Visual analytics combines automated analysis with interactive visualizations for effective understanding, reasoning and decision making on the basis of a very large and complex dataset" [55]. Icke [56], Keim [57], and Sun et al [58] provide good overviews of the state of current research on visual analytics. While there are obviously many different areas of investigation ongoing in visual analytics research there are three particular areas that are highly relevant to the current effort for IEEA: (1) methods to facilitate user interaction with data; (2) specific types of visualizations and frameworks; and (3) data reduction and handling of large amounts of data.

Visual analytics research on methods for interacting with data to extract useful insights provides some guidance to the current research on IEEA. As a visual metaphor for describing how data interaction should be applied to gain insights, Shneiderman et al.[59] proposed the famous information seeking mantra: "Overview first, zoom/filter, details on demand". Highlighting the need for coupling numerical and algorithmic data analysis with interactive visual interfaces to gain insights during visual data exploration Keim et al. [60] later extended the mantra. The revised version called the visual analysis mantra was: "Analyze first, show the important, zoom/filter, analyze further, details on demands". Prototype applications for IEEA follow the visual analysis mantra as a guideline.

As discussed in the Section 2.2.4, the IEEA framework extends prior research on RSC and RMACS to include human interaction considerations, drawing inspiration from the visual analytics process. The visual analytics process, introduced by Keim et al. [55], is characterized through interaction between data, visualizations, models of the data, and the users, in order to discover knowledge. The process, shown in Figure 2-9, begins by transforming the data (e.g. filtering, sampling, cleaning) so that it can be analyzed further. Next, visual or algorithmic analysis methods are applied to explore the data. When visual data exploration is used, users directly interact with the visual interface to analyze and explore the data. When automatic analysis methods are applied, approaches such as regression modeling or pattern matching are used to estimate models for characterizing the data.

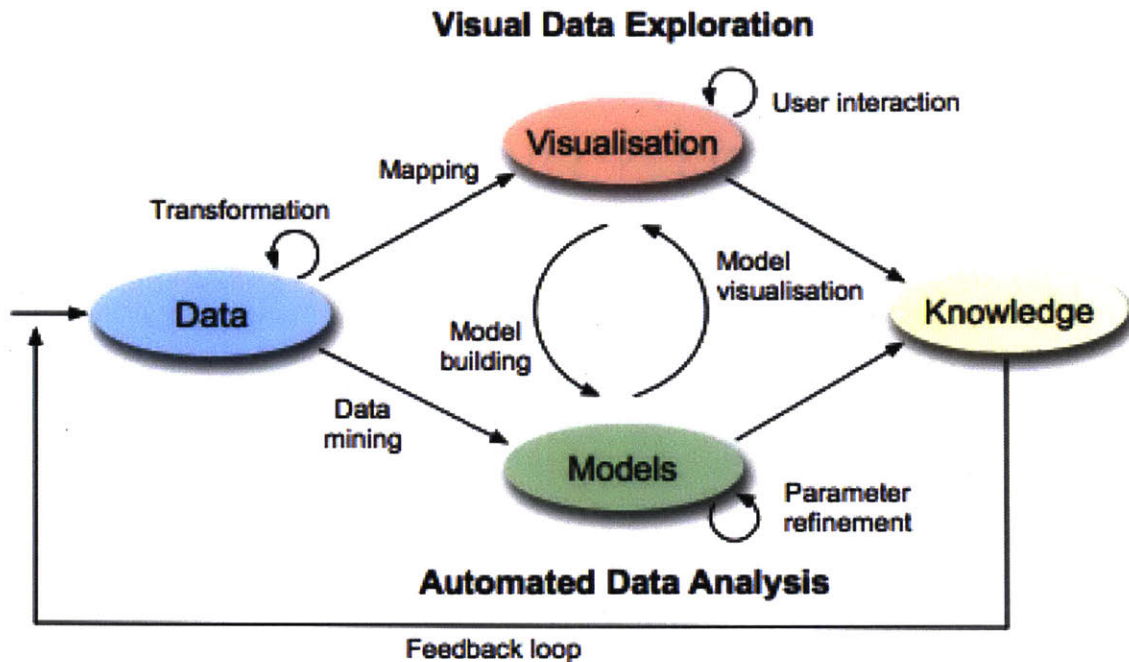


Figure 2-9: Visual analytics process by Keim et al. [55]

Numerous frameworks for developing interactive visualization applications exist. Prototype applications for IEEA utilize prior research on Data-Driven Documents (D3), a representation-transparent framework for rapid development of online data visualizations developed by the Stanford Visualization Group [61]. D3 is used for producing dynamic, interactive data visualizations in web browsers and is the successor to earlier work on the Protovis framework [55][62]. It allows for direct manipulation and modification of any elements in the document object model (DOM) and enables smooth animation and user interactions.

Several other concepts from research within the visual analytics community are also relevant to the current research on IEEA. Data reduction techniques like those described by Fodor [63], Holbrey [64], and Liu et al. [65] are necessary because computational resources will always be a constraint on complex decision problems like those encountered in systems engineering analysis. Problems arise in computing, storing, and transmitting the data from a database or local storage device to the user display. Several researchers have also focused on the problem of how to visualize large sets of data once they reach the user display [66,67,68,69]. Others have focused more on the specific types of visualizations such as scatter plots, tree maps and parallel coordinate diagrams [70,71,72,73,74].

The background provided by this prior work is extremely important to solving the problem at hand, but for decision making in systems engineering applications the most important factor is arguably whether the decision maker understands and can find insights in the multi-faceted data they are viewing. Recent work on multiple coordinated visualizations has been geared towards determining how user displays with multiple

types of information can be used to extract deeper meaning from the data [75,76,77]. This is a potentially useful technique for the types of systems engineering interfaces that are prototype applications generated for this research.

Many engineers make decisions about constraints on performance parameters (outputs) without considering how that restricts ranges on design variables (inputs). As an example, if an engineer sets a resolution requirement on a satellite that requires a certain optical aperture size, this will likely restrict the set of available launch vehicles that can take that satellite into orbit due to fairing size restrictions. Supplying the engineer with immediate visual feedback on the consequences of their decisions could be enabled through simultaneous coordinated views of both the design and performance spaces. Enabling users to interact with their data through visual interfaces of this type is an area of active research [78,79,80]. Integrating data interaction, algorithmic analysis and advance engineering methods is seen as key to the current research effort on IEEA.

2.4 Existing Systems Engineering Applications

The final area of background research to be explored as part of this thesis is currently available conceptual system design applications. Web-based applications similar to prototypes developed for this research are not a new concept and have previously been discussed in works by Heer [80] and in applications specific to engineering design by Liu [81]. As noted previously, Spero [21] performed a holistic review of 81 existing tradespace exploration applications and found wide variability in the implementations and types of functions performed by various existing applications. The Framework for Assessing Cost and Technology (FACT), currently in use by the U.S. Marine Corps Systems Command (MCSC), is an example of a web-based systems engineering application reviewed by Spero [82,83,84]. While FACT is a sophisticated tool for performing tradespace exploration it does not specifically consider multiple stakeholder needs or future changes in context and/or mission. The FACT application takes the traditional view of exploring tradeoffs in system attributes for user-selected restrictions or filters on design variables and performance variable ranges.

The first published mention of a web-based application that performs tradespace exploration coupled with a value-driven design approach is given by Sitterle [85]. Sitterle also gives some consideration to multiple sets of future stakeholder needs and how those may drive future system utility. This work primarily discusses a candidate engineering workflow and how the utility of a system can be computed through ranking of its attributes, but also demonstrates how this might look in a prototype web-based tool. Though they are both web-based applications, neither FACT nor the application described by Sitterle focus on interactive visualization as it is thought of in the current research on IEEA. Interactive visualizations for IEEA are frequently both an input (typically mouse clicks) and an output (graphs of the data) that facilitate communication between the human user and the computer.

2.5 Summary and Working Hypotheses

The preceding review of the currently published literature shows a clear gap between the capabilities desired by those that must acquire and/or design complex systems and available methods and applications that can be readily implemented to tackle the problem. Changes in the design, context, or stakeholder needs impact the value proposition and thus the “success” of a system. EEA constructs can be applied to analyze these problems in ways that current tradespace exploration methods cannot, but come at the expense of a more complex data set to be analyzed by the decision maker. Possibilities for addressing these challenges through extensions of EEA exist by leveraging research in advanced systems engineering methods and visual analytics. In particular, there are currently three working hypotheses regarding Interactive Epoch Era Analysis (IEEA) that align with the proposed research questions:

1. When engaged in the design process, the relative contributions of the two components of visual analytic applications (representation and interaction) will provide a benefit to analysts in different ways depending on task type. Further, individual differences in personality and spatial reasoning ability between users may also affect performance.
2. A new interactive design framework that incorporates EEA and explicitly considers human interaction will fundamentally enable new capabilities and insights, resulting in superior dynamic strategies for sustaining long-run system value.
3. Coupling algorithmic data analysis with interactive visual interfaces will enhance an analyst’s ability to analyze, comprehend and communicate decisions when exploring system trades with IEEA.

Several contributions are expected from this research. At its conclusion, this research should illuminate ways to better enable decision makers to design complex systems that deliver sustained value to stakeholders. New approaches should seek ways to balance system, context, and expectations over time, during engineering design, evaluation and selection, given human cognitive and perceptual limitations. This will require the development of a rigorous framework for applying EEA that explicitly considers how analysts will interact with data and make decisions. It is also envisioned that this research will contribute novel approaches that incorporate interactive visualizations to facilitate human cognition and improve decision-making. The IEEA framework and associated processes, methods, metrics and prototype applications will be evaluated using case studies and a controlled human-subjects experiment.

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3.0 Considerations for Visual Analytic Applications

As the volume and scale of data available to engineering analysts increases, new opportunities for knowledge discovery begin to emerge. However, these new opportunities also come with new challenges associated with using that data effectively for decision-making. The development of effective visual analytic tools provides a way to aid analysts that must wade through large amounts of complex data to find insights. These tools integrate the capabilities of the human with the analytic power of machines to help find hidden insights and enable reasoning, sense making and cognition.

The preceding chapter described some of the literature that has been reviewed as part of this thesis research that lays the theoretical foundation for ways visual analytics research can help address these challenges. This chapter goes into further detail about how an integrated, interactive visualization application for IEEA can be developed based on existing theory, methods and technologies from research in the field of visual analytics. A key consideration throughout will be issues of scalability to large-scale problems like those found in practice. This chapter will also demonstrate how this research can be tied together in a simplified example application, implemented in software, that lays the groundwork for more sophisticated, IEEA-specific interactive visualizations described in the Chapter 4.

3.1 Potential Benefits of Visual Analytics Systems

As discussed in the literature review of the preceding chapter, visual analytic systems have been shown to provide a benefit to analysts and decision-makers working in many different problem domains including finance, healthcare and infrastructure planning. Depending on the particular domain or task, visual analytic applications can provide different types of benefits to the user. In one frequently cited work on information visualization, Card et al. [86] suggest six primary mechanisms by which interactive visualizations can improve cognition as shown in detail in Table 3-1. In short, they suggest that interactive visualizations can:

1. Increase working memory and processing resources available to the users
2. Reduce search for information
3. Enhance the detection of patterns using visual representations
4. Enable perceptual inference operations
5. Enable perceptual attention mechanisms for monitoring
6. Encode information in a manipulable medium

Table 3-1: How information visualization amplifies cognition (from Card et al. [86] Table 1.3)

Increased Resources	
High-bandwidth hierarchical interaction	The human moving gaze system partitions limited channel capacity so that it combines high spatial resolution and wide aperture in sensing visual environments [87]
Parallel perceptual processing	Some attributes of visualization can be processed in parallel compared to text, which is serial.
Offload work from cognitive to perceptual system	Some cognitive inferences done symbolically can be recorded into inferences done with simple perceptual operations [88]
Expanded working memory	Visualizations can expand the working memory available for solving a problem [89]
Expanded storage of information	Visualizations can be used to store massive amounts of information in a quickly accessible form (e.g. maps)
Reduced Search	
Locality of processing	Visualizations group information used together, reducing search [88]
High data density	Visualizations can often represent a large amount of data in a small space [90]
Spatially indexed addressing	By grouping data about an object, visualizations can avoid symbolic labels [88]
Enhanced Recognition of Patterns	
Recognition instead of recall	Recognizing information generated by a visualization is easier than recalling that information by the user.
Abstraction and aggregation	Visualizations simplify and organize information, supplying higher centers with aggregated forms of information through abstraction and selective omission [87,91]
Visual schemata for organization	Visually organizing data by structural relationships (e.g. by time) enhances patterns.
Value, relationship, trend	Visualizations can be constructed to enhance patterns at all three levels [92]
Perceptual Inference	
Visual representations make some problems obvious	Visualizations can support a large number of perceptual inferences that are extremely easy for humans [88].
Graphical computations	Visualizations can enable complex specialized graphical computations [93]
Perceptual Monitoring	
	Visualizations can allow for monitoring of a large number of potential events if the display is organized so that these stand out by appearance or motion.
Manipulability Medium	
	Unlike static diagrams, visualizations can allow exploration of a space of parameter values and can amplify user operations.

Interactive visualization has also demonstrated its usefulness in industry practice. One particular problem domain that shares many similarities with the type of decision-making problems addressed in this thesis is business analytics, which has seen increasing adoption of interactive data analysis tools in recent years. In a recent research study, Krensky [94] noted a number of positive benefits from the use of interactive tools in business analytics applications. Specifically, he states that, “adopters of interactive visualization achieve faster decision making, greater data access, and stronger user

engagement, in addition to desirable results in several other metrics”. The metrics cited in the study include:

1. 70% of interactive visualization adopters improved **collaboration** and knowledge sharing
2. 64% of interactive visualization adopters improved user **trust** in underlying data
3. Interactive visualization users **engage data more frequently** for decision making
4. Interactive visualizes are 150% more likely than static visualizers to be **satisfied** with ease-of-use of analytical tools

There are clearly many potential benefits to a well-designed interactive visualization application. Still, interactive applications must be tailored to the task at hand in a way that results in improved decision-making by driving the analytical experience and by fostering user engagement and satisfaction. The following section will describe in further detail the specific components of a visual analytics system and how they can best be tailored for application to system design problems using EEA.

3.2 Components of Visual Analytics Systems

Prior applications of EEA have relied largely on analytic tools that are designed to execute sequentially and output a result at the end in the form of static figures that summarize the results of a pre-defined analysis. The interactive applications demonstrated in this thesis are distinctly different in that they are designed to run continuously with human interruption and redirection. This leads to unique complexities associated with their development. In addition, in order to realize the true advantages of having a human in the loop, custom interaction methods and abstract visual representations must be tailored to the task at hand. This may require the ability to develop new visualization types from lower-level visual elements rather than toolkit-specific abstractions like charts generated in Excel or Matlab, for example.

Issues of scalability must also be considered when designing customized visualizations and interaction methods. These issues are driven by both the pixel limitations of the screen and the need for low-latency interactivity. Efficient and well-integrated infrastructure is critical to visual analytics applications that require a high degree of interactivity. Three main parts of visual analytic systems will be discussed in this section: data management, visual representations, and interaction methods.

3.2.1 Data Structures, Management and Transformation

Central to all visual analytic systems are data that is either some type of real-world data, collected from a sensor or survey for instance, or data that is generated dynamically by a computer model. For the purpose of the research described in this thesis the focus is on the latter (i.e. model-generated data). In order to be used effectively by a visual analytics system this data once generated must be stored to allow efficient access.

Depending on the level of sophistication required, data storage methods can range from simple flat files, or more structured file formats up to more complex relational databases. Spreadsheet-like flat files, such as Comma Separated Values (CSV), are frequently used because of simplicity and versatility, but are limited to a tabular structure and lack data typing. More structured file formats like XML or javascript object notation (JSON) overcome these disadvantages as they allow both data typing and more complex hierarchical data structures. Relational databases are also frequently used in visual analytics platforms and allow for one or more tables where individual data records are identified by unique keys. Regardless of storage method used, to be interactively visualized, data must be queried and loaded into memory which can impact interactive performance. Each of these data storage methods varies in capability and interactive performance and was applied to various interactive visualization prototypes demonstrated in this thesis.

Given a data storage method, the purpose of the visual analytic system is then to transform raw data to views, and enable some manipulation of the data through human interaction. To enable decision-making, the next question that must be answered then is, what is the best way to transform the data into a representation that an analyst can comprehend? The question is non-trivial because a conceptual architecture is user-driven as well as data-driven. As noted by Keim [55], several architectural models exist for mapping data to a representation or visual interface that are applicable in various problem domains. Haber & McNabb [95] described a dataflow model for the visualization pipeline as shown in Figure 3-1 that processes raw data into a displayable image or animation using three transformations: data enrichment/enhancement, visualization mapping, and rendering. Building on research on the visualization pipeline, the information visualization reference model shown in Figure 3-2 was developed by Chi [96] and revised by Card et al [86]. This conceptual architecture considers the possibility that user interaction can occur throughout the stages of the visualization pipeline. Keim notes that, “all the well-known implementations of information visualization systems and toolkits adhere to this model”. The research and various prototypes presented in this thesis also apply a similar process.

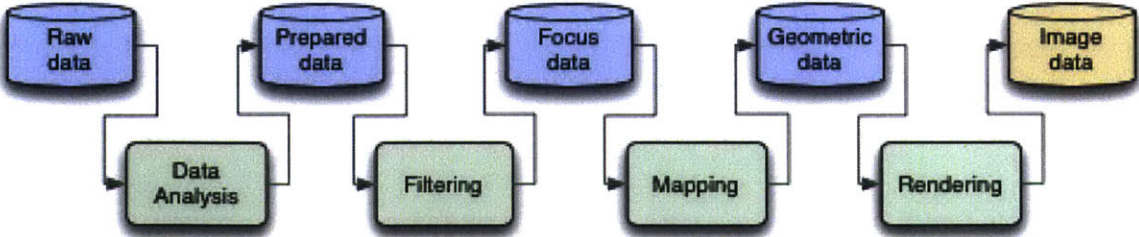


Figure 3-1: The Visualization Pipeline [97,55]

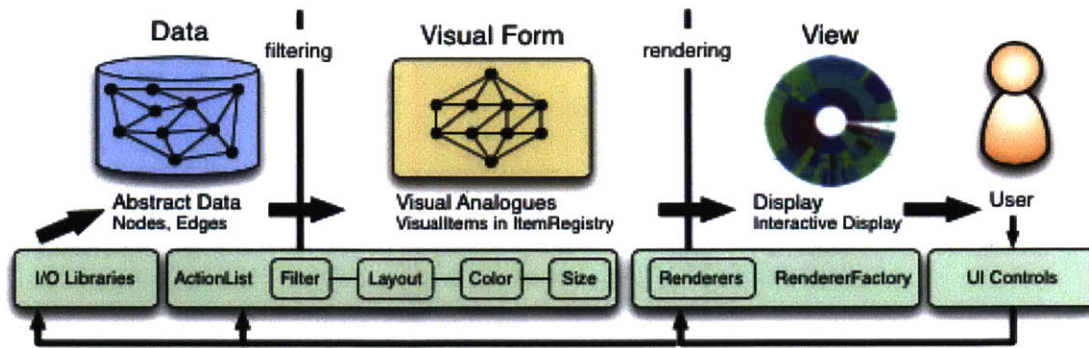


Figure 3-2: The Information Visualization Reference Model [98,55]

3.2.1.1 Data Reduction and Aggregation

When working with datasets with a manageable number of points, visualizations can directly depict each data point in a dataset to allow the viewer to observe and detect interesting patterns in the data. Large amounts of data, however, create limitations associated with available screen sizes and ability to render data quickly, which can lead to problems. When there is more data than there are pixels on the screen data can become obfuscated and effective culling methods or more sophisticated visual representations are necessary to present data succinctly. Effective interaction may also be necessary to allow the user to change between different views or levels of abstraction of the dataset. The limited screen space effectively creates both a spatial and an information density problem [55,99,99]

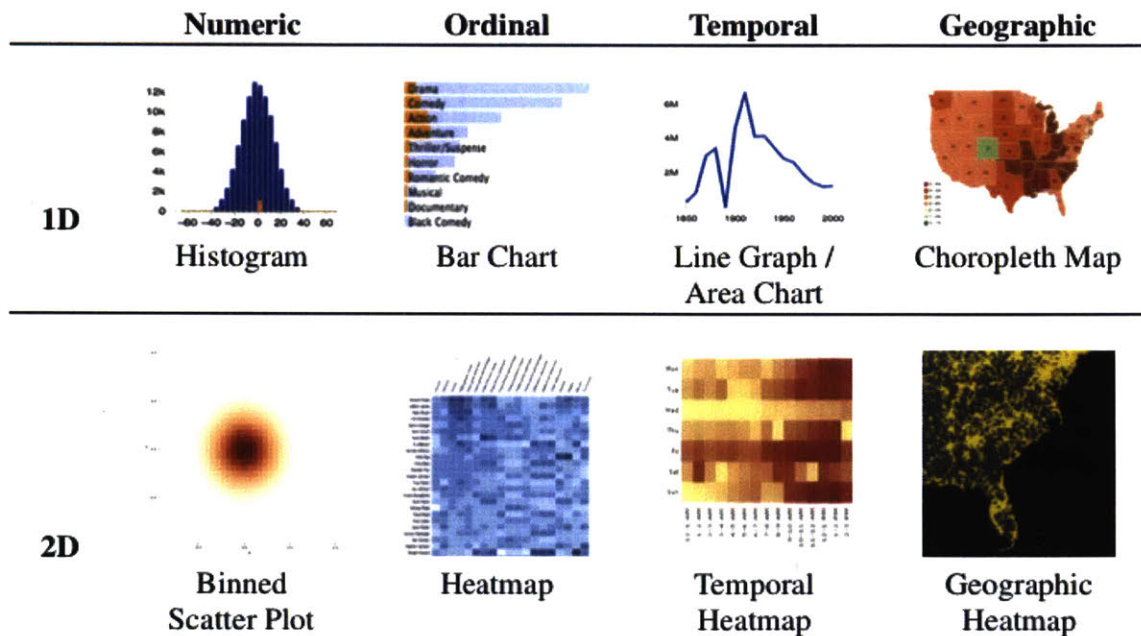
Problems with rendering and the scalability of visualizations and other encoded visual information can be improved upon using techniques that do not require every single data point to be drawn. Liu points out that, “Perceptual and interactive scalability should be limited by the chosen resolution of the visualized data, not the number of records,” and summarizes several techniques past researchers have applied to reduce the pixel density of visualizations including **(1) filtering;** **(2) sampling;** **(3) binned aggregation;** and **(4) model-fitting** [65].

Filtering is a commonly applied technique to reduce the problem to a subset of the original data. This is accomplished by placing bounds on the data dimensions such that not all of it is displayed at once, which could be overwhelming to a decision maker. Likewise, sampling is a technique for reducing the amount of data displayed to the user by systematically or randomly drawing a subset of the points to create a reduced set for display. Sampling has the potential downside of unintentionally concealing features of the dataset that may correspond to rare events. These are oftentimes the very data points in which a decision maker is most interested.

Filtering and sampling are often used in practice because they are relatively easy to implement and do not require any changes in the standard visualizations types that

would be used for a larger dataset. Both techniques are useful, but other techniques that allow all the data to be visualized should also be considered. Binned aggregation is powerful in that it allows a decision maker to observe global patterns in the data as well as local features that may be hidden by filtering or sampling [65]. Examples of how data can be binned to display various types of information based on data type and dimensionality are shown in Table 3-2. In tradespace exploration and EEA, which often use 2-D scatter plots to display data, one example of binned aggregation is to project the data for each axis into a 1-D histograms. Alternatively, the data could also be aggregated into smaller 2-D bins with the density of points encoded by color in a way similar to the examples shown in Table 3-2. Examples of how these techniques can be applied to a simplified tradespace exploration problem are demonstrated in prototype visualization tools described in Section 3.5.1.

Table 3-2: Example visualizations for binned data (from Lui et al. [65])



Model-fitting is another approach that can be applied to reduce the resources required to visualize a large dataset. Examples of model-fitting include simple regression models or complex surrogate models that reduce the dataset to representative equations. Model-fitting can be a powerful technique, but computing an appropriate model can sometimes be computationally expensive. Models also typically have some amount of error in how well they represent the underlying data and this must be carefully considered when using their outputs for the purpose of decision-making.

3.2.1.2 Online Analytical Processing (OLAP)

Online Analytical Processing (OLAP) is an approach for creating abstract representations of high-dimensional datasets with large numbers of data points. Using OLAP, data is pre-processed into data cubes that store large numbers of data points aggregated by dimension and/or hierarchical level (e.g. minute, hour, day). An analyst can then explore the dataset through visualizations that use the smaller 1D, 2D or 3D data projections that can be represented in computer memory in a more compact way. As shown in Figure 3-3, data represented as a hypercube can be rapidly manipulated using a small number of operations including: dicing, slicing, roll-ups, drill-downs and pivots. Conceptualizing a dataset in this way effectively results in a tradeoff in precision in exchange for speed which is often more desirable for applications that require a high degree of interactivity.

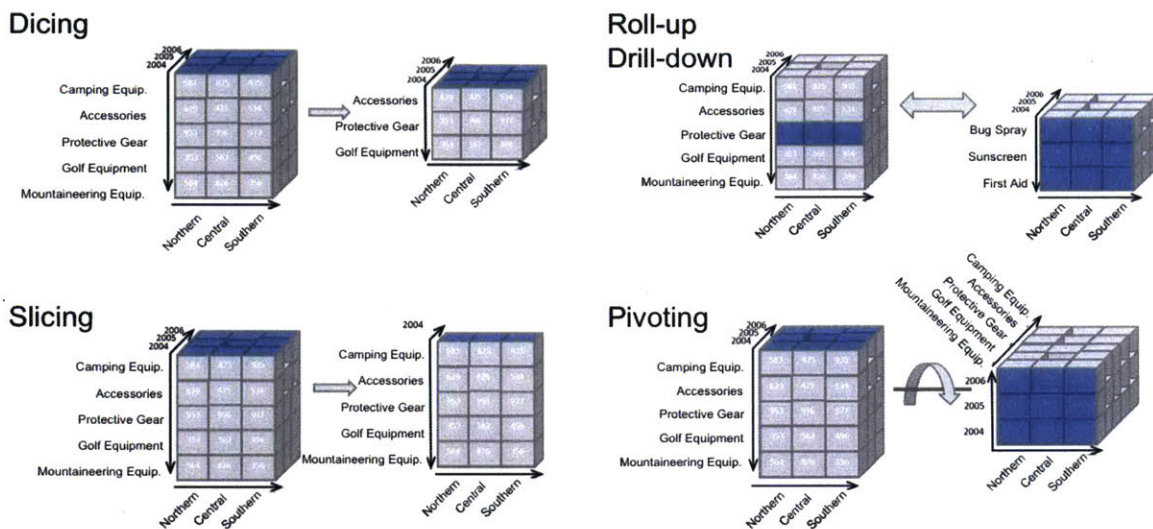


Figure 3-3: OLAP operations on data hypercube (Adapted from [100])

OLAP is frequently applied in data mining and other exploratory analysis applications with large amounts of data. These datasets are often stored in relational databases with multiple tables connected by keys, but can also be as simple as a spreadsheet with records stored in each row and with columns representing different attributes or properties of the data. In fact, pivot tables generated in MS Excel are a simplified example of a common use of OLAP for summarizing data. Another notable application of OLAP is its successful use in business intelligence (BI) applications to parse large amounts of sales, cost and other data to evaluate trends and inform business decisions.

For IEEA, the benefit of OLAP is that it enables a user to view data from multiple points of view and quickly uncover previously undiscovered relationships and patterns within the dataset. A decision-maker looking at a large number of candidate designs across a large possible epoch space can apply OLAP techniques to slice, dice, drill down,

roll up or compute pivots of the hyper-dimensional data cube representing design alternatives over epochs and eras. This allows them to easily extract data that is of interest to them which, in turn, enables better intuition on which to base decisions.

3.2.2 Visualization and Data Representation

As a component of this research, several concepts related to visualization and how graphical representations of data can be used to facilitate the analytical reasoning process have been examined. No single visualization can tell a decision-maker everything they need to know while applying IEEA. A suite of various visualization types that show different aspects of the data must therefore be considered. This section discusses technologies and methods that will enable new ways of examining the complex data that is generated during IEEA.

3.2.2.1 Visualization Methods / Interactive Applications in D3

Charts, graphs and other visual representations are powerful ways of communicating information to users. Data visualizations are essentially abstract representations of quantitative information that can range from simple scatter plots and bar charts to more sophisticated visualizations customized for a particular data set. The purpose is to allow a viewer to observe higher-level patterns or meaning by encoding the information in the visual elements using position, shape, color, etc. An influential study by Cleveland and McGill [101] ranked several basic types of visual information in the order that viewers are best able to decode and comprehend them. Their ranking can be summarized as follows:

1. Position along a common scale (e.g. scatter plot)
2. Position on identical but nonaligned scales (e.g. multiple scatter plots)
3. Length (e.g. bar chart)
4. Angle & Slope (e.g. pie chart)
5. Area (e.g. bubble charts)
6. Volume, density, and color saturation (e.g. heatmaps)
7. Color hue)

Many of these basic chart types are incorporated into IEEA-related visualizations where appropriate. However, sometimes the nature of the data being examined calls for a more unique or customized visualization. Many toolkit-specific abstractions provide a limited vocabulary for creating visualization and are sometimes limited to a palette of standard charts and annotations. For this research, versatile methods are needed that enable custom interactive visualizations to be created within a web page and dynamically rendered and manipulated with a web browser. Data-Driven Documents (D3), a JavaScript library developed by researchers in the Stanford Visualization Group, is the most recent outcome of a decade of research to achieve exactly that outcome [61]. Some examples of interactive visualizations developed using D3 are shown in Figure 3-4 below.

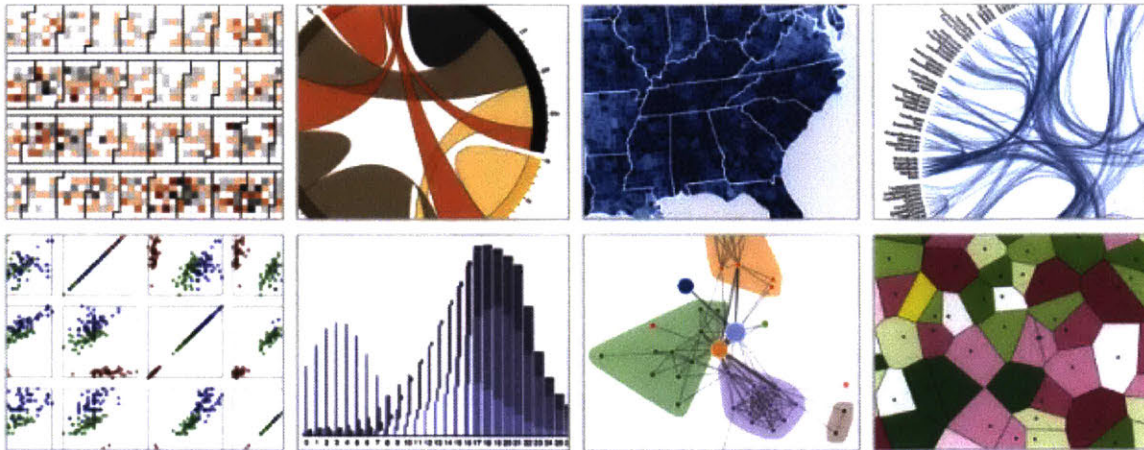


Figure 3-4: Example interactive visualizations built with D3 [61]

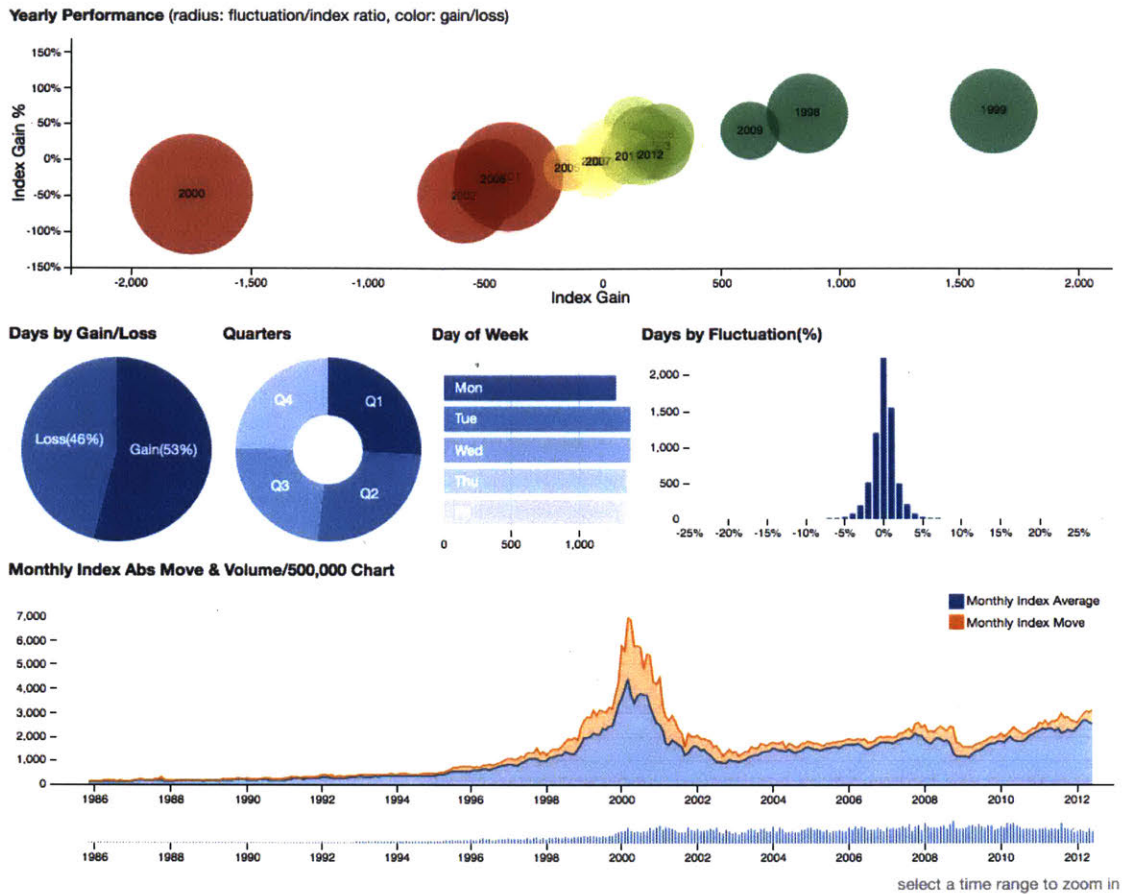
D3 is based on prior development dating back to the release of Prefuse [102], a visualization toolkit that used Java plug-ins to render data in the browser, in 2005. Prefuse was superseded by Flare [103], which used a combination of ActionScript and Flash plug-ins for rendering, in 2007 and then later Protovis in 2009. The objective of Protovis was to achieve improvements over its predecessors in terms of the level of expressiveness, efficiency and accessibility. Efficiency, in this case, refers to the level of “effort required to specify a visualization”, and accessibility refers to the “effort required to learn and modify the representation” [62].

Like Protoviz, D3 uses JavaScript embedded within an HTML webpage to generate scalable vector graphics (SVG) through the specification of “visualizations as hierarchy of marks with visual properties” [62] (e.g. shape, color, value) and behaviors (e.g. events, animated transitions) by selectively binding functions of the input data to document elements. This allows relatively large datasets to be bound to document elements that are automatically updated as the underlying data is manipulated or changed. Improvements in performance are achieved through a focus on adherence to web standards like the SVG, HTML5, and CSS standards. This also results in fewer integration issues with other technologies that are frequently problematic when developing visual analytic systems. D3 has achieved wide acceptance in both industry and academia due to improvements in flexibility, expressiveness, and performance over its predecessors. The use of D3 as the means for generating interactive visualizations for IEEA enables expressiveness for new types of visual representations that aren’t currently possible with higher-level languages like Matlab. It also provides flexibility for future research in this area as our understanding of design methods and human performance progresses.

3.2.2.2 Multiple Coordinated Visualization

As discussed previously, simultaneously depiction on a computer screen of every single data point can be difficult, if not impossible, when working with a large data set. This can be due to either the large number of data points, the dimensionality, or the complexity of the data represented. To derive insights from the data often requires the user then to examine subsets of the data using methods like those described in Section 3.2.1.1. The user may also seek to comprehend the data by looking at roll-ups or projections of the data using OLAP as described in Section 3.2.1.2. Another alternative is to simultaneously examine multiple views of the data represented on separate charts, each representing some aspect of the larger data set, similar to the example shown in Figure 3-5. These are referred to as coordinated multiple views and have been the subject of a significant amount of prior research [75,76,77].

Nasdaq 100 Index 1985/11/01-2012/06/29



All records selected. Please click on the graph to apply filters.

Date	Open	Close	Change	Volume
1985/11				
11/01/1985	115.48	116.28	0.80	900900
11/04/1985	116.28	116.04	-0.24	753400

Figure 3-5: Nasdaq performance data shown in multiple coordinated views [104]

Multiple coordinated views can be used in exploratory visualization to more effectively expose relationships in the underlying data. Coordinated views are separate, independent views of a given set of data that serve as complementary representations, and may aid in identifying patterns as well as errors in the data. The individual views of the data are not intended for use in isolation, but rather to be combined to generate insights. The primary purpose of coordinated visualizations is to allow improved understanding through user interaction with different simultaneous representations of the data [75]. While choosing which combinations of views to use in order to generate insights can be complicated, several guidelines, including compactness and diversity of the visualizations, have been discussed in prior literature [76]. In this thesis, many of the

prototype applications incorporate multiple coordinated views connected through brushing and linking interactions as an approach for facilitating deeper understanding of the data.

3.2.3 Interaction Techniques

The third and final component of interactive visualization systems discussed in the section is the interaction component itself. The study of these components is rooted in human computer interaction (HCI) and User Experience (UX) related research. If the use of a visual analytics application is thought of as a collaborative effort between a human and computer, visualization is a mechanism that allows the computer to communicate with the user and the interactive component allows that dialog in the other direction.

Interaction with a visual interface can be intended to aid the user in different ways. The interactive components may produce “details on demand” such as when a point is hovered over to activate a tooltip or interactive text with additional information. They may also trigger changes in the visual representation or how it is displayed such as when a dimensional assignment is changed or a filter is applied to one of several charts in an application with multiple coordinated views as shown in the example in Figure 3-6. Though defining a single taxonomy of interaction methods is challenging [59,99,105], several specific types of interactive elements/methods are incorporated into prototype applications demonstrated in this research:

- Mouse events (hovering, clicking, mouse over/out)
- Brushing and linking between coordinated views
- Filtering / Dynamic query
- Panning and Zooming
- Highlighting or clickable interactive text
- Sliders
- Radio buttons and check boxes
- Direct manipulation of charts

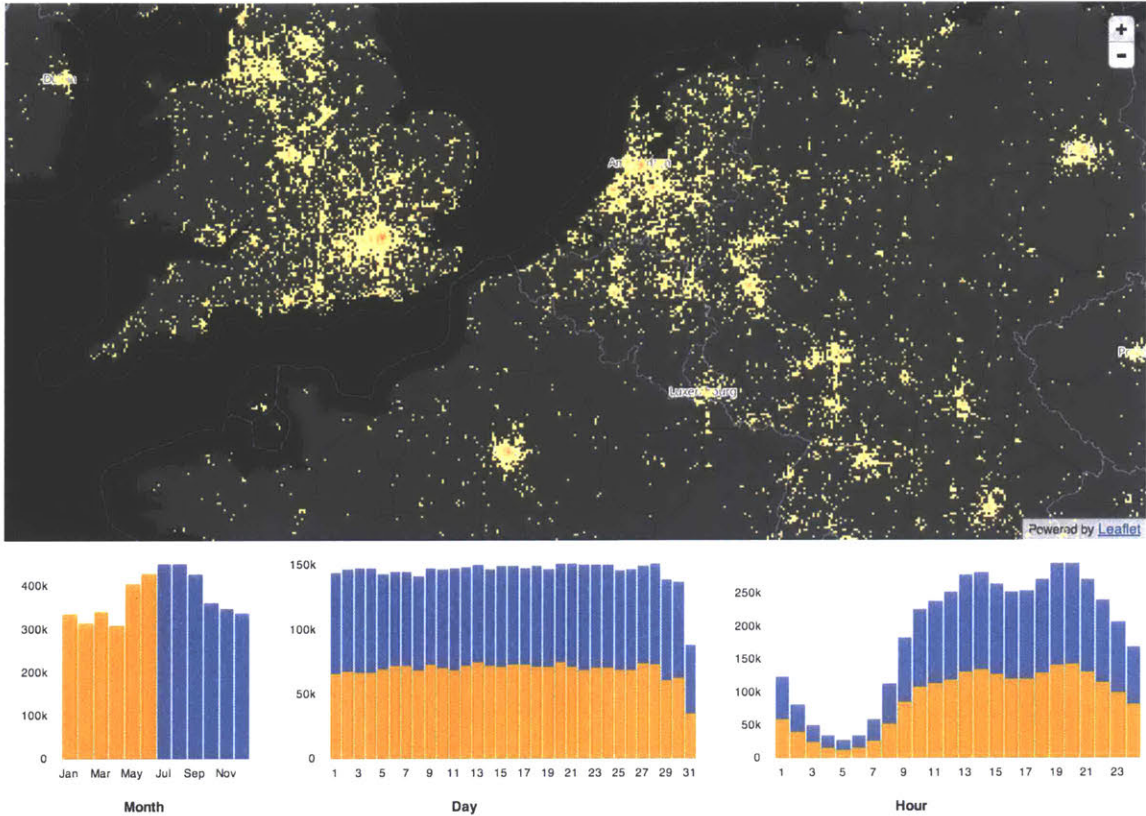


Figure 3-6: Brushing and linking between four coordinated views displaying different dimensions [106]

Latency is a significant issue that drives that the perception of the usability of an interactive application. An often-cited rule of thumb dating back decades to original research by Miller is that in interactive applications the screen should update within 100 milliseconds following a user action [55,91,107]. Increasing the delay between the interaction and the response tends to increase the probability that a user can perceive the delay as shown in Figure 3-7.

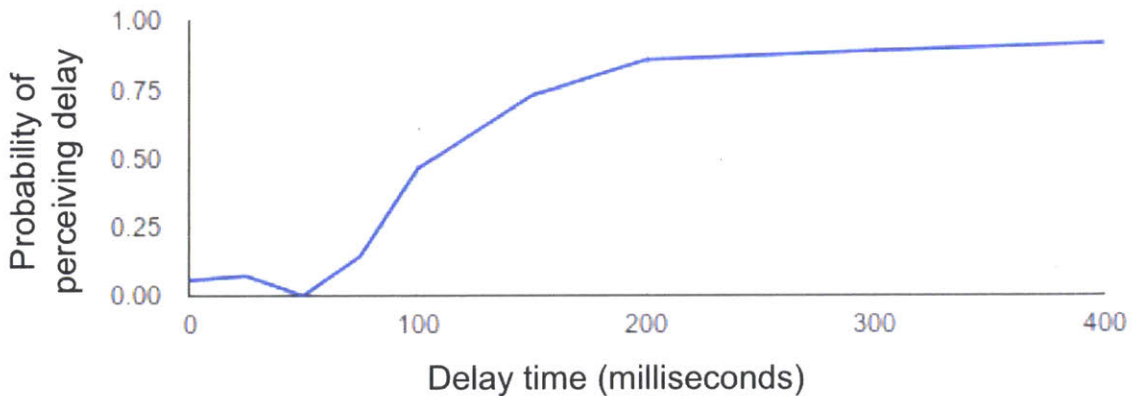


Figure 3-7: User perception of interactive delay time [108]

Though the subjective threshold of 100 millisecond is the most frequently mentioned rule in regards to latency, additional guidance on performance is described by Nielsen in his book on usability engineering [109]:

- *“0.1 second is about the limit for having the user feel that the system is reacting instantaneously, meaning that no special feedback is necessary except to display the result”.*
- *“1.0 second is about the limit for the user's flow of thought to stay uninterrupted, even though the user will notice the delay. Normally, no special feedback is necessary during delays of more than 0.1 but less than 1.0 second, but the user does lose the feeling of operating directly on the data”.*
- *“10 seconds is about the limit for keeping the user's attention focused on the dialogue. For longer delays, users will want to perform other tasks while waiting for the computer to finish, so they should be given feedback indicating when the computer expects to be done. Feedback during the delay is especially important if the response time is likely to be highly variable, since users will then not know what to expect”.*

Depending on how an analysis tool is architected, longer delays in interaction are sometimes unavoidable. Feedback for these longer delays as described in the third bullet above can include elements such as percent-done progress indicators. Such indicators can let the user know that a request has been heard, interpreted, and accepted by the computer and that the system is now working to provide an answer [110]. Though interactive response time that is too slow is the usability concern that is more frequently discussed, it should also be noted that a computer response could also be too fast. A response that is too fast may prevent the user from perceiving a change. For instance, when the purpose of an interaction is to change the visual representation or update its underlying data, animated transitions can be useful for facilitating a user's perception of changes when transitioning between visual representations [111]. It is worth cautioning that while animation can make an interface more intuitive and/or engaging, it can also become a distraction (e.g. “chart junk”) if used ineffectively [90].

3.3 Guidance on Visual Analytic Tool Design

The following subsections describe some of the existing heuristic and methodological guidance on the design of visual analytics applications.

3.3.1 Visual Analytics Process and Mantra

The visual analytics process, shown in Figure 3-8, describes how knowledge is obtained through close coupling of visual and algorithmic data analysis. It enables this discovery through interaction, visualizations and models to help make sense of the data. However, by itself it does not provide details on how an interactive data analysis application should be designed. For researchers and practitioners who seek to develop novel visual analytic applications some heuristic and methodological guidance exists

from various sources. This section reviews some of the guidance that describes how interactive visual interfaces can be effectively implemented to engage the user in collaboration.

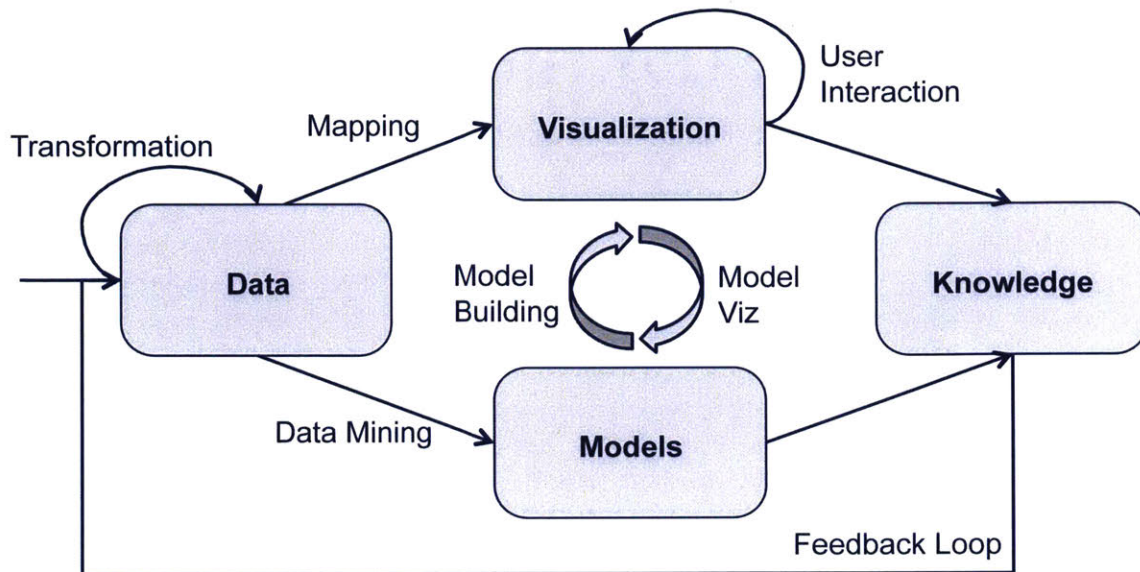


Figure 3-8: Visual Analytics Process (adapted from Keim et al. [55])

The visual information-seeking mantra, proposed by Shneiderman, is a frequently cited example of how applications for data visualization should be designed. The mantra states that an interactive visualization should provide:

“Overview first,
zoom and filter,
then details-on-demand” [59].

Shneiderman further suggests that the four tasks mentioned in the mantra plus three additional ones (relate, history, extract) can be used as a taxonomy to guide researchers and practitioners developing new applications.

Arguing that as a dataset becomes larger, overview visualizations may be less effective at summarizing data without losing interesting patterns, Keim proposed the visual analysis mantra. The visual analysis mantra extends Shneiderman’s guidance to:

“Analyze first,
show the important,
zoom/filter,
analyze further,
details on demands” [55].

As the mantra suggests, for large datasets, a well-designed interactive application must perform some analysis to identify the important aspects of the data and provide an

overview of those data first so that the user can understand the general context. Establishing the appropriate context early allows the user to decide what information is unnecessary for the task at hand so they can exclude it from further analysis.

To exclude data points from consideration, a user can use zooming and filtering operations. Filtering removes data that meets certain criteria, often values or ranges on data dimensions, established by the user. Though it is often thought of merely as an operation that alters the size of visual elements on the screen, zooming actually has a function similar to that of filtering. Filtering removes points from the visual representation, but zooming alters the view into the data. As summarized by Craft, zooming “removes extraneous information from the visual field” by changing the “representational vantage point” on the data. In this way, by reducing or aggregating the data on screen to “manageable inputs by simplification and organization” the user is better able to discern “meaningful patterns for interpretation and decision-making” [112]. The Resnikoff Principle of Selective Omission, which describes how humans simplify and organize sensory information and abstract it to draw conclusions, describes this effect in detail [86].

The final step in the mantra, “details on demand”, helps overcome limitations placed on the interactive application by the number of available pixels on the computer screen. With large datasets sometimes only a small fraction of the data can be represented on screen by a visual element and often the element is intended as an aggregate representation with associated metadata or details that can be drilled-down into. Interactions such as clicking or hovering the mouse pointer over a data point to pull up additional details without altering the visual representation can be useful. One example, shown in Figure 3-9, shows how additional details about a data point in a scatter plot can be made available to a user by interactively highlighting a tooltip when the mouse is hovered over a point. More details on this particular visualization, used in single and multi-epoch analysis, will be provided in Chapter 4.

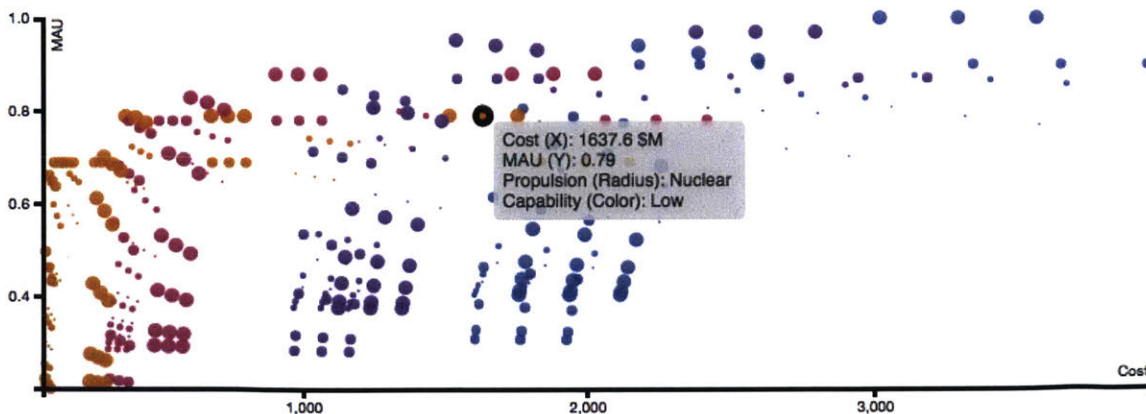


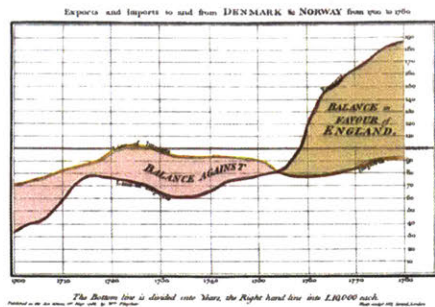
Figure 3-9: Details on demand from hovering mouse over a data point

It should be noted that it is not strictly necessary that an interactive visualization application incorporate all of the steps of the visual analysis mantra. Shneiderman described the information-seeking mantra as “descriptive and exploratory” and neither he nor Keim suggest that the extended version described by the visual analysis mantra is necessarily intended as prescriptive guidance [86]. Many visualization developers do treat it as a prescriptive principle, however [112].

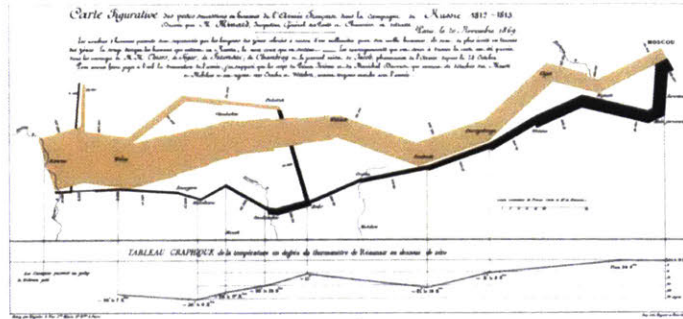
3.3.2 Information Design and Effective Visual Communication of Data

The preceding section was focused on reviewing some of the heuristic and methodological guidance that exists on the processes that visual analytic tools should follow in order to be effective. This section focuses on available recommendations for how information can be displayed efficiently and effectively in a visual representation. Specifically, this section will attempt to summarize some of the guidance from the closely related fields of information design, informational graphics and data visualization.

The purpose of an abstract visual depiction of data is to allow a viewer to make comparisons, determine causal relationships and gain deeper insights [113]. The design of graphical representations of data goes back centuries. Playfair is often credited with the development of several diagram types that he used to represent economic data, including the line, area, bar and pie charts. Other historical examples that are often cited as well-designed, information-dense visualizations are Snow’s map of the 1850’s London cholera outbreak, Minard’s diagram of Napoleon’s 1812 Russian campaign, and Nightingale’s coxcomb diagram depicting mortality rates [90]. In order to make more effective visualizations for IEEE, however, we don’t want to duplicate existing diagrams, but rather determine what makes these visualizations good at conveying insights and what heuristics or generalizations can we derive from them?



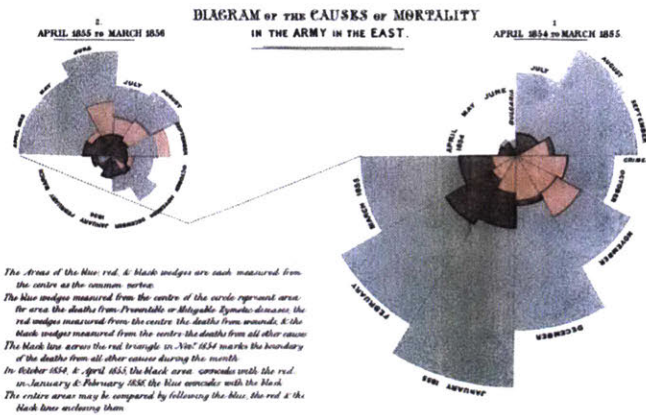
A



C



B



D

Figure 3-10: Historical applications of information visualizations (a) Playfair's trade-balance time-series chart [114]; (b) Snow's spot maps of London cholera outbreak in 1850s [90]; (c) Minard's 1861 diagram depicting Napoleon's Russian campaign of 1812 [115]; (d) Nightingale's coxcomb diagram of army mortality rates [116]

The field of information design aims to provide some best practices for the display of information in ways that aid exploration and/or explanation of data to guide decision-making, not simply generate attractive or artistic visualizations. Put another way, visual representations should amplify cognition, not simply provide pretty pictures. Elements in a visualization or graphical representation should be presented in such a way that they enhance a viewer's ability to observe relationships, patterns and meaning in data. Card et al. provide a good summary of the purpose of information design as expressed by Edward Tufte, a thought leader in this area: "Edward Tufte articulates this discipline best. According to Tufte, excellence in graphics consists of complex ideas communicated with clarity, precision, and efficiency. Graphical displays should induce the viewer to think about the substance, present many numbers in a small space, make large data sets coherent, encourage the eye to compare different pieces of data, reveal the data at several levels of detail, from a broad overview to the fine structure." [86]

Tufte's large body of work in this field has also provided some additional heuristics and methods for displaying information that may be considered in the design of

the interactive visualizations in this research. Similar to the concept of “overview first” Tufte suggests that a chart or visualization should “presented in the space of an eye-span” with every visual element representing a data value. These **data-dense illustrations** should allow a viewer to closely examine details or detect patterns and data trends when viewed more generally [117].

Another key concept introduced by Tufte was the concept of **data-ink ratio** [90]. He suggests that a visualization designer should minimize the data-ink ratio which, put another way, suggests that a designer should maximize the amount of a visualization devoted to data and eliminate visual elements that are redundant. Tufte provides the bar chart shown in Figure 3-11 as an example of a graphic that encodes only a single numerical value using six redundant visual elements. *“Redundant data-ink depicts the same number over and over. The labeled, shaded bar of the bar chart, for example, unambiguously locates the altitude in six separate ways (any five of the six can be erased and the sixth will still indicate the height): as the (1) height of the left line, (2) height of shading, (3) height of right line, (4) position of top horizontal line, (5) position (not content) of number at bar’s top, and (6) the number itself.”* [90]

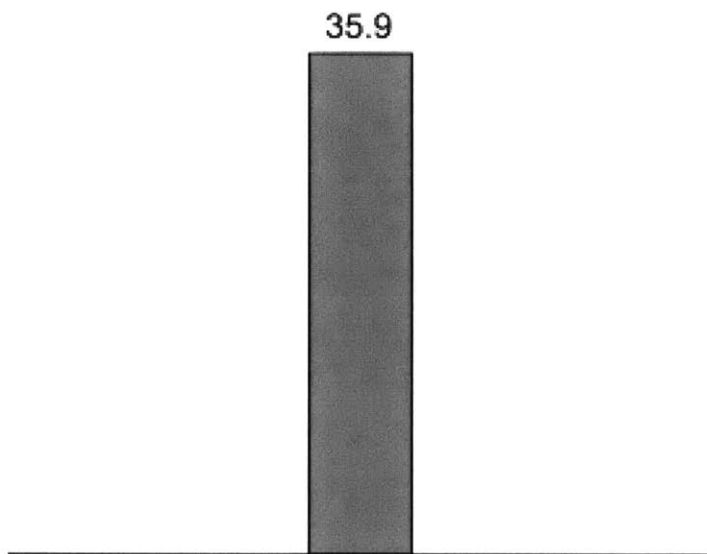


Figure 3-11: Tufte's Bar chart example [90]

Redundant representations or non-informative decoration is what Tufte refers to as “**chart junk**” because visual elements are being used and don’t display any new or useful information [90]. It should be noted that some of the interactive visualization applications developed for IEEA and presented in Chapter 4 use text labels on visual elements, such as bars in a bar graph. This is not a deviation from Tufte’s principle of minimal ink because these labels provide information about the dimension represented not redundant information about the length of the bar itself.

A final method suggested by Tufte that has been incorporated into prototype applications for IEEA is the use of **small multiples**. Small multiples of a single type of graph with

variations in parameters are repeated to allow a viewer to make comparisons between them when viewing high-dimensional data. This can be a useful approach when plotting multiple data series on the same chart would be too visually cluttered or when the individual data ranges are quite different. An example of the use of small multiples is shown in Figure 3-12.

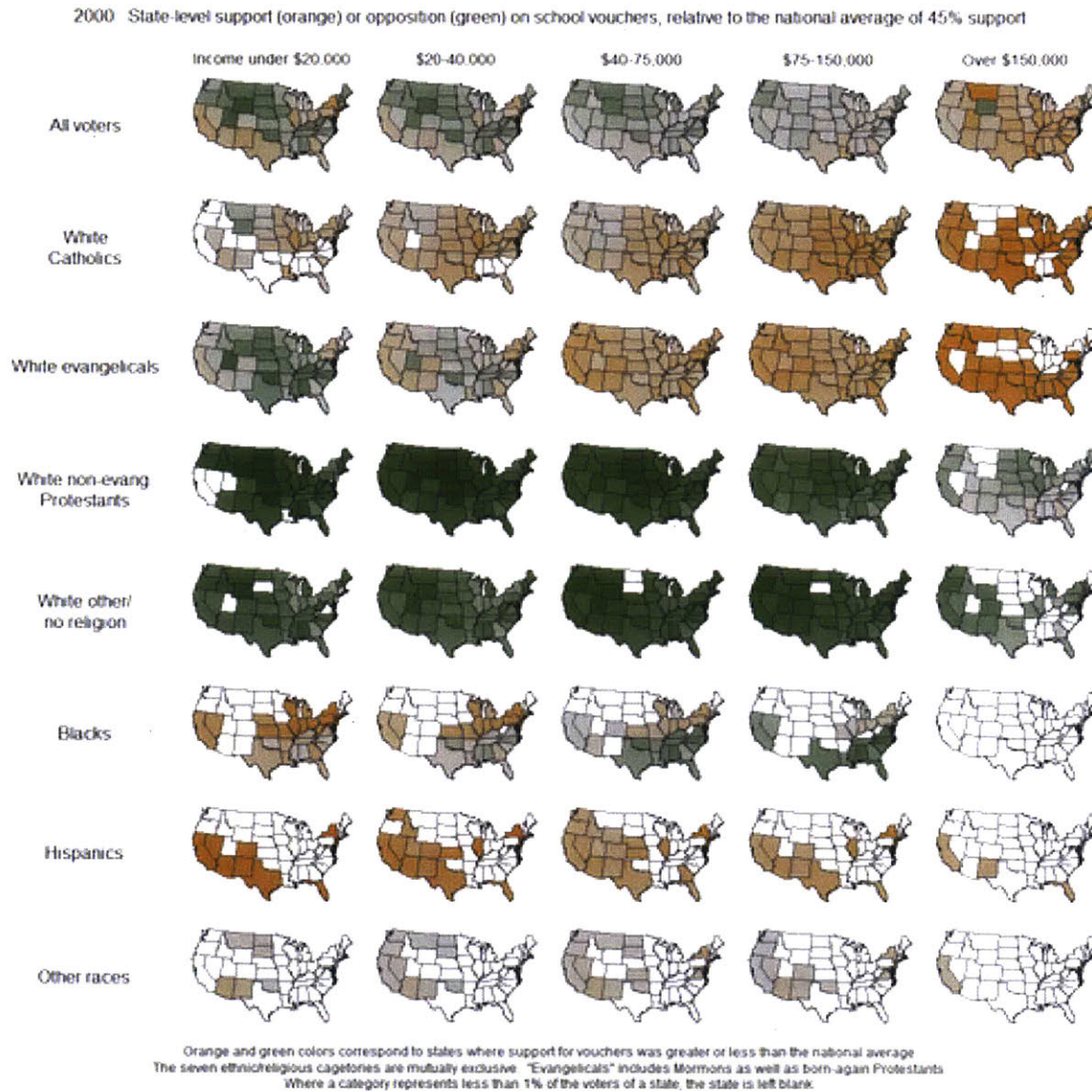


Figure 3-12: Example of the use of small multiples [118]

3.4 Integrated Application for Operationalizing IEEA

Thus far this chapter has focused on the potential benefits, some specific components, as well as heuristic and methodological guidance for applying research from the field of visual analytics to enable an interactive implementation of EEA. The next issue to address is how all of this can be practically integrated into a software implementation for IEEA with considerations for scalability. Specifically, since many of the technologies used to create prior visual analytics application are intended for web-browser-based implementation, a similar software architecture is considered here.

Web-based applications are often separated into two layers called the front-end and the back-end. The front end, also referred to as the client-side or presentation layer, provides the interface through which the user views visualizations and interacts with them via a web browser. The front-end software is typically implemented in browser interpretable languages like HTML, CSS and JavaScript that allows static content, styling and dynamic content to be separated. The back end, also referred to as the server-side or data access layer, provides data processing and storage. It is frequently implemented using scripting languages like Python, though in this research testing has also been performed with R and Matlab-based modules as shown in Figure 3-13.

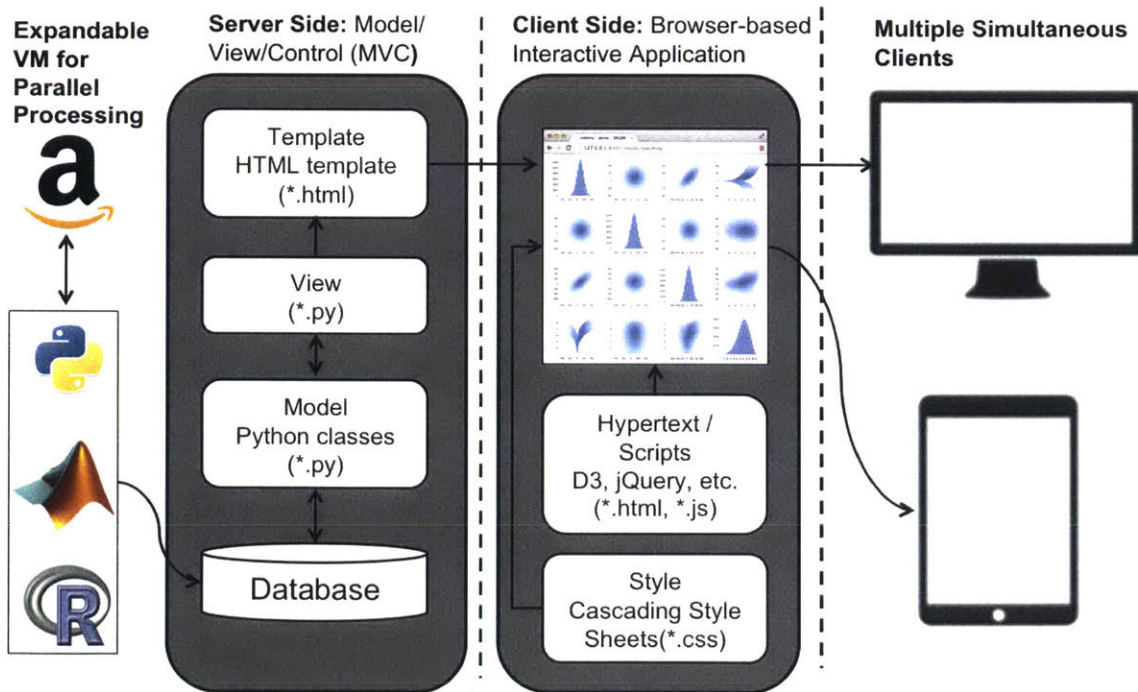


Figure 3-13: Web-based Architecture

Figure 3-13 also shows the use of a model–view–controller (MVC) software design pattern as it was implemented using the Django framework in this research [119]. The model and controller are part of the back-end and the view is associated with the front end. As used here, the user interacts with elements in the view via the web browser which triggers commands to the controller on the back-end. The controller interprets those commands for the model and then the model updates the data to send back to the front-end to update the view as detailed in Figure 3-14. The updated data can be the result of a database query or in some cases generated in real time.

By separating functionality in this way large amounts of data can be generated and summarized by the back-end so that it can be used by the front-end user interface in a more manageable way. This is often necessary because memory and processing limitations on the client-side as well as issues associated with data transmission latency. It is also necessary as a matter of practicality because if you send so much data to the front-end that the browser can't handle it, it is likely that the viewer can't visualize it anyway. In other words, even if you could render all the data to the screen it would be more than the viewer could reasonably perceive at one time.

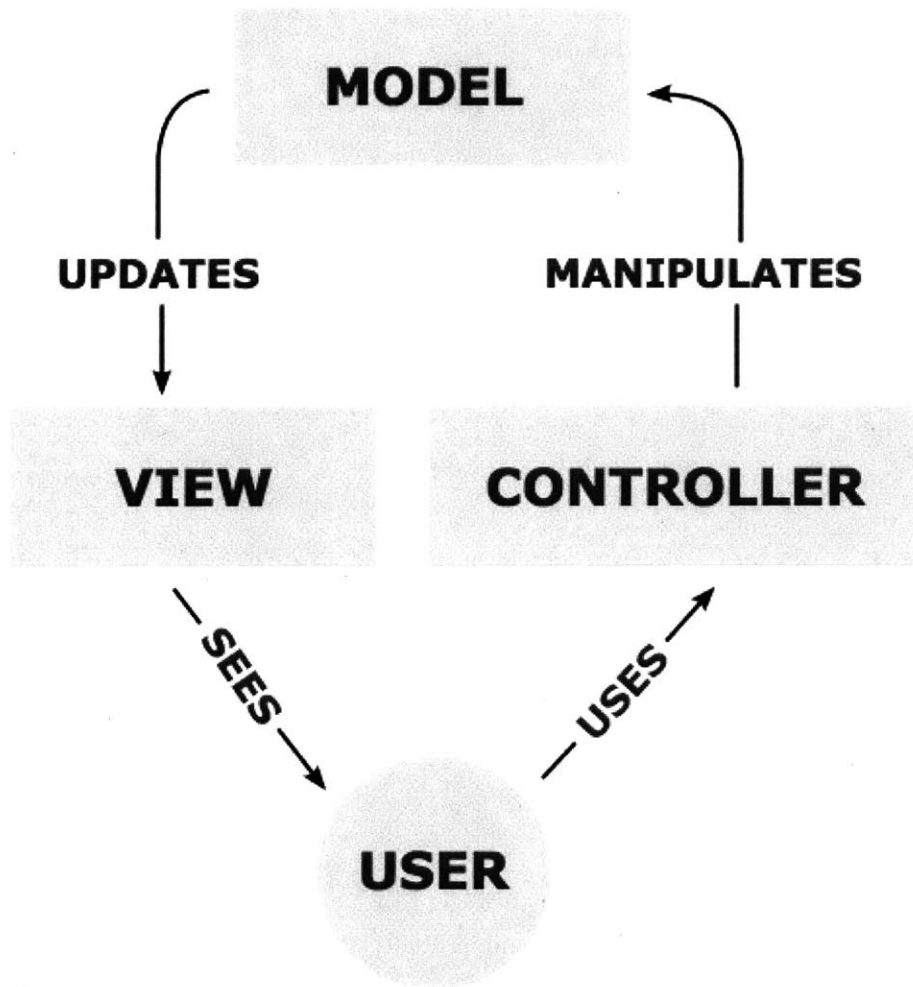


Figure 3-14: Model-View-Controller architecture [120]

3.5 Integrated Application Preliminary Case Study

As a preliminary test, the integrated application described in this chapter was applied to a previously developed case study. The case study implements parametric models of an Earth-imaging satellite constellation to analyze trades in performance and cost. Design variables such as number of satellites per orbital plane, number of planes, optics size, and altitude are evaluated against measures of performance such as optical resolution, revisit time, percent global coverage, and lifecycle cost. For brevity, details of the case study will not be repeated here, but interested readers are referred to the earlier paper for detailed descriptions of the case study implementation [121]. The case study, originally analyzed using traditional tradespace exploration (TSE) and multidisciplinary optimization (MDO) techniques, was extended to demonstrate EEA. To that end, 3 different system stakeholders, each with differing value functions, and 2 possible future contexts were considered. This results in 6 unique epochs. The lone context variable

evaluated was whether or not an electromagnetic disturbance occurs, resulting in diminished value delivery of the satellite constellation.

3.5.1 Web Browser-based Application Demonstration

Implementation of an IEEA demonstration needs to draw on a combination of the techniques described in this chapter. This means that IEEA needs to take into account the practicality of representing large amounts of data effectively given scarce communication resources (e.g., limited spatial or temporal resolutions due to hardware or software constraints) [74]. Given the volume and complexity of the data that needs to be analyzed, IEEA methods and tools should be capable of providing data to the decision-maker in a way that enhances cognition. A demonstration of the above discussed techniques for coordinated visualization, OLAP and data reduction method was implemented in a prototype web browser-based tool similar to those described by Sitterle et al.[85]. To improve information cognition by the user, guidelines for effective coordinated visualization [76] and animated data transitions [122] were applied.

Figure 3-15 shows a screenshot of scatter plot representations of the available design alternatives. The two scatter plots correspond to design values evaluated in epoch 1, the baseline case, and epoch 5 which represents a situation in which stakeholder preferences for individual performance attributes has changed. The left-hand plot shows the utility versus cost of the alternatives evaluated in epoch 1. The right-hand plot shows the same alternatives evaluated in epoch 5 and it is clear that the resulting tradespace has been distorted, relative to epoch 1, due to a change in the stakeholder preferences. To further convey that information to the user, histograms of cost and utility are displayed with each plot.

If a decision-maker believes that it is possible that the system will experience both epoch 1 and 5 over the course of its lifetime, then they might prefer a design to be Pareto efficient in both epochs. However, since the shape of the tradespace has changed between epochs 1 and 5, a decision-maker should not necessarily expect designs that were previously on the Pareto front to remain there in the new epoch. Applying the concepts of brushing and linking between coordinated visualizations, the user can interactively draw a lasso around Pareto efficient designs of interest in epoch 5 and receive immediate feedback on where those same designs appear in epoch 1.

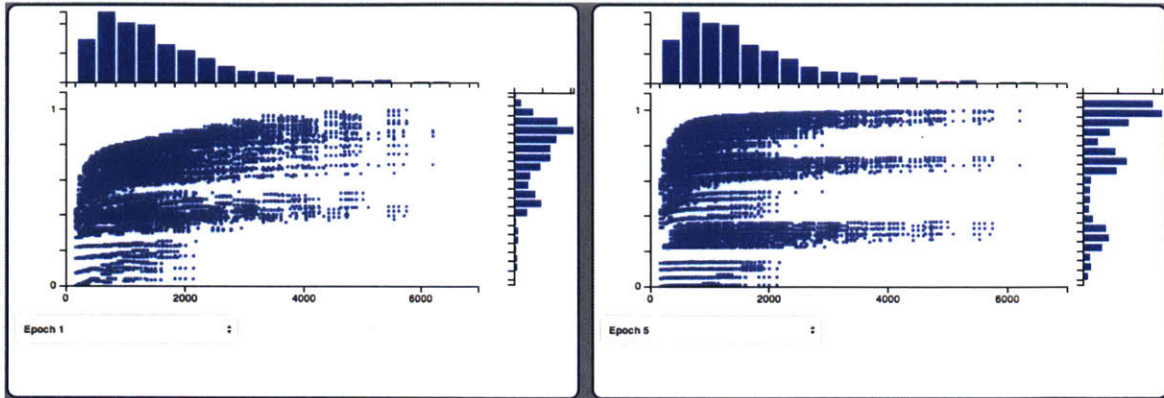


Figure 3-15: Web-based tool showing coordinated scatter plots and histograms

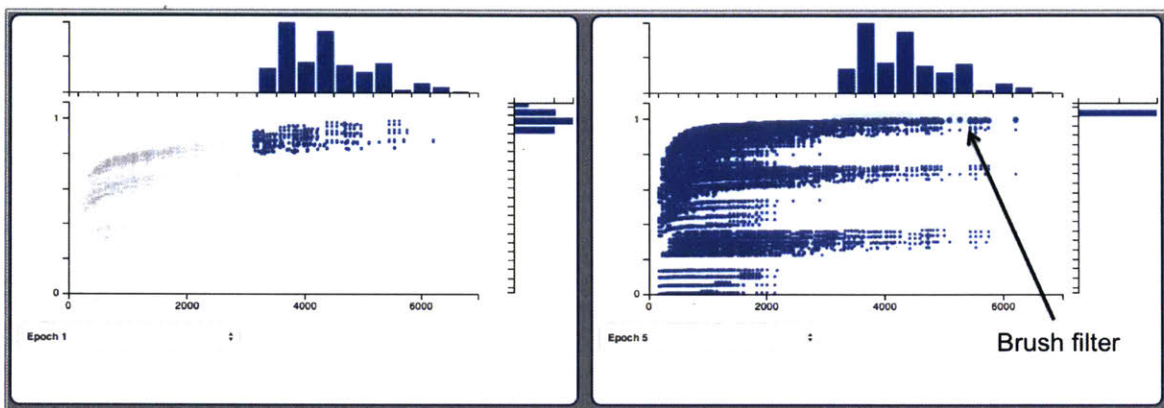


Figure 3-16: Brushing to filter designs across coordinated views

As shown in Figure 3-16, all of the coordinated visualizations (e.g., epoch 1) are updated simultaneously to reflect only the designs selected through brushing (in epoch 5). It is clear from the combined visualizations that while the selected points are Pareto efficient in epoch 5, some of them deviate from the Pareto front in epoch 1. User cognition of this conclusion is reinforced by the utility histograms to the right of each scatter plot that show that the tight distribution of utilities in epoch 5 are now more spread out in epoch 1. In addition to brushing, a user can also interactively filter data by clicking on the histogram bars to effectively filter out all but a selected slice of the data. As shown in Figure 3-17, by clicking on the y-axis histogram of the right hand figure, data not associated with those bars is grayed out in the coordinated views.

Enhanced understanding of the impacts of a decision on multiple epochs can be very powerful as demonstrated in this example. Much of that power is driven by the rapid response between visualizations provided to the user interacting with them. As previously discussed, OLAP techniques can be applied to slice, dice, drill down, roll up or compute pivots of the hyper-dimensional data cube representing design alternatives over epochs and eras. For the example presented here, Crossfilter, a JavaScript library which functions like a client-side OLAP server, has been used to allow rapid filtering between scatter plot views and to accelerate grouping of the thousands of data points into

the aggregated histogram views. Latency between user interactions with any visualization and the resulting updates in corresponding visualizations is on the order of milliseconds. This provides a seamless interactive experience, which should facilitate improved user cognition of the data on which they will base their decisions.

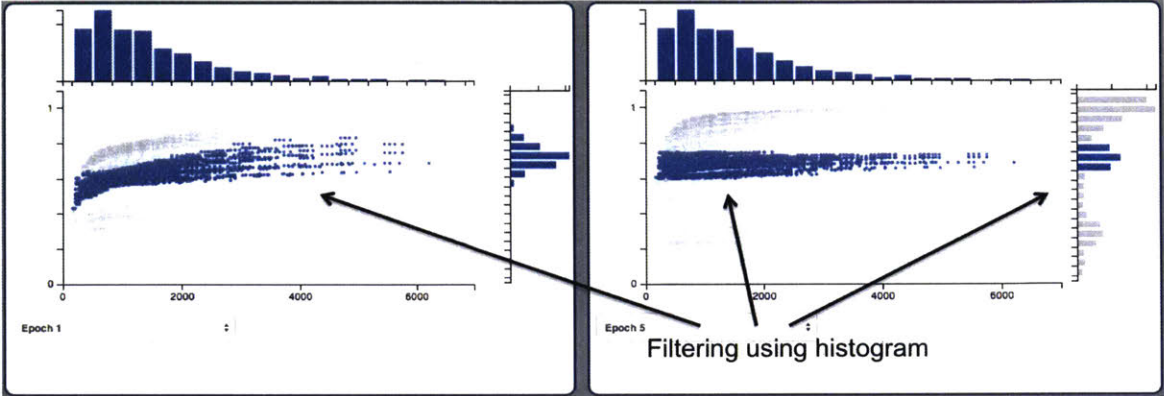


Figure 3-17: Coordinated views showing histogram bin selection to slice data using OLAP

As the number of design alternatives and epochs grow, interactive coordinated visualizations can slow, as processing and rendering of the data becomes the limiting factor. Data reduction techniques can be applied in these situations to keep the large amounts of data from becoming unduly burdensome. Some past examples of EEA case studies utilizing filtering or sampling approaches include applications in the transportation [123] and space domains [124]. Since these approaches have the possible implication of concealing important information, we would prefer to use methods that allow us to represent all of the data. Binned aggregation can allow us to accomplish this aim.

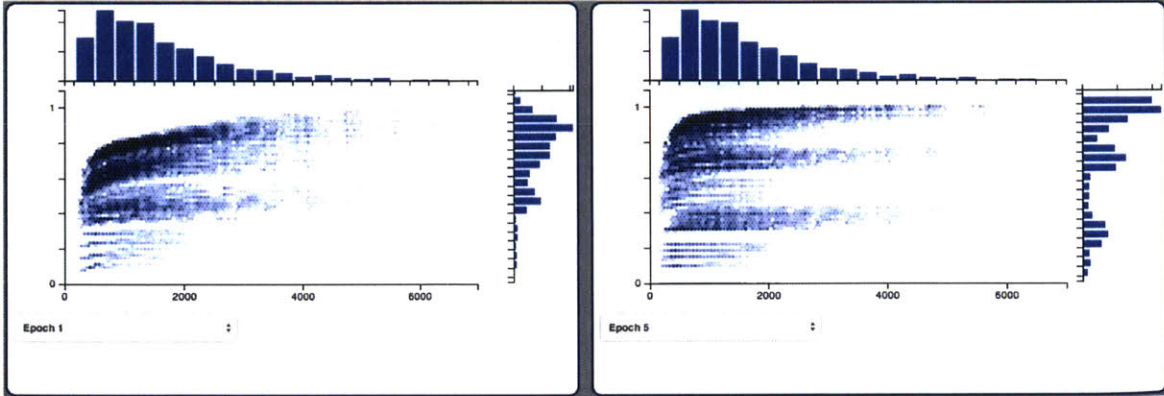


Figure 3-18: Coordinated scatter plot views with 2-D binned aggregation

In the prior examples, histograms were a type of binned aggregation, since they reduced the larger set of points to a smaller set of rectangular bars reflecting the amount of data in each bin. This required projection of the 2-D data into a 1-D space. To allow a decision-maker to more fully appreciate the underlying features of the tradespace, we would ideally like to represent the 2-D data with fewer polygons, while simultaneously not reducing the number of dimensions. One technique for accomplishing this is to group data into rectangular bins and encode the density of points using color hue [65,71]. Some researchers have argued that hexagonal bins can better represent data over rectangular bins, to aid a user's interpretation [72]. A key rationale is the fact that hexagons have more sides and thus look more like circles, while providing a regular tessellation of a 2-D surface. Implementing the hexagonal binning approach on the running example significantly reduces the number of polygons required, and thus speeds up interactive rendering. A screenshot of the example implemented with hexagonal binning is shown in Figure 3-18.

3.6 Chapter Summary

This chapter has outlined some of the potential benefits, primary components and suggested guidance for the development of visual analytic systems. Further, this chapter goes on to describe how this information can be applied to guide the operationalization of IEEA and demonstrates how these methods can be integrated into a coherent, interactive application that can be used in data exploration problems like those found when applying EEA. Though this is a small-scale demonstration, this integrated application has been developed with scalability in mind.

It is hypothesized in this research that the extension of interactive visualizations like these to system design problems with lifecycle uncertainty will result in improved comprehension of the nature of underlying trades and improve a designer's ability to communicate their decision-making rationale. In the next chapter, the IEEA framework, the processes that comprise it and more detailed prototype interactive visualizations that have been developed to implement and test it using the methods described in this chapter will be discussed. Chapter 5 will demonstrate, via a controlled human subjects experiment, that the application of interactive tools like these have a measurable impact on human performance when performing design tasks like those that are the focus of this thesis.

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4.0 Interactive Epoch Era Analysis (IEEA) Framework

As discussed previously in the review of existing literature, a couple of frameworks for applying EEA constructs have been introduced in prior research. One of the key challenges associated with applying these existing frameworks (e.g. RSC, RMACS) to some real-world problems is the lack of detailed prescriptive guidance on how a human-in-the-loop should interact with the potentially large amounts of data produced and how that data should be analyzed, visually or algorithmically, to generate insights. Some of the specific theories, methods and available technologies from existing research in the field of visual analytics described in the preceding chapter can be incorporated to improve the application of EEA constructs.

Building on prior EEA frameworks, in this chapter the Interactive Epoch Era Analysis (IEEA) Framework is introduced as a prescriptive framework for applying EEA that explicitly considers human interaction based on the visual analytics process to guide effective decision making. Coupling the new framework with interactive visualization techniques will enable comprehension of the nature underlying trades when working with the large multivariate EEA data sets. For relevant analysis processes of the new framework several interactive visualization are described. These visualizations were developed based on both prior visual analytics research and feedback from industry practitioners.

4.1 Introduction

Epoch-Era Analysis (EEA) is designed to clarify the effects of changing contexts over time on the perceived value of a system in a structured way [125,126]. Prior research studies have demonstrated the usefulness of Epoch-Era Analysis (EEA) in, but some challenges still remain in practical applications for informing decision-making in many real world problems. Although methods for implementing EEA constructs have been developed and applied in case studies, a prescriptive framework that explicitly considers human interaction does not yet exist. Furthermore, EEA can result in large, multivariate datasets that are difficult to manage, visualize and perform analysis on. This is precisely where effective visualization and analysis techniques are needed, to help make informed decisions, design successful strategies for value sustainment, and derive valuable insights from the data.

Interactive Epoch-Era Analysis (IEEA) is an iterative framework for concept exploration that provides a means of applying EEA constructs while controlling growth in data scale and dimensionality [127,128]. Further, IEEA leverages interactive visualization because prior visual analytics research has demonstrated that when performing exploratory analysis, like early-phase system concept selection, an analyst can gain a deeper understanding of the underlying data. This can lead to improved comprehension and decision-making. Consequently, the extension of interactive visualization to system design problems with lifecycle uncertainty can result in improved

comprehension of the nature of underlying trades and can also simultaneously improve a designer's ability to communicate their decision-making rationale to others.

4.2 Interactive Epoch Era Analysis (IEEA) Related Data

A key challenge to applying EEA-constructs in large-scale problems is the volume and complexity of the data that is both an input to the study or an output of it. This section provides an overview of the types of data that is often present in EEA studies. A high-level overview of some of the important pieces of data that may come up are shown in Figure 4-1 and some details on the various data types are included below.

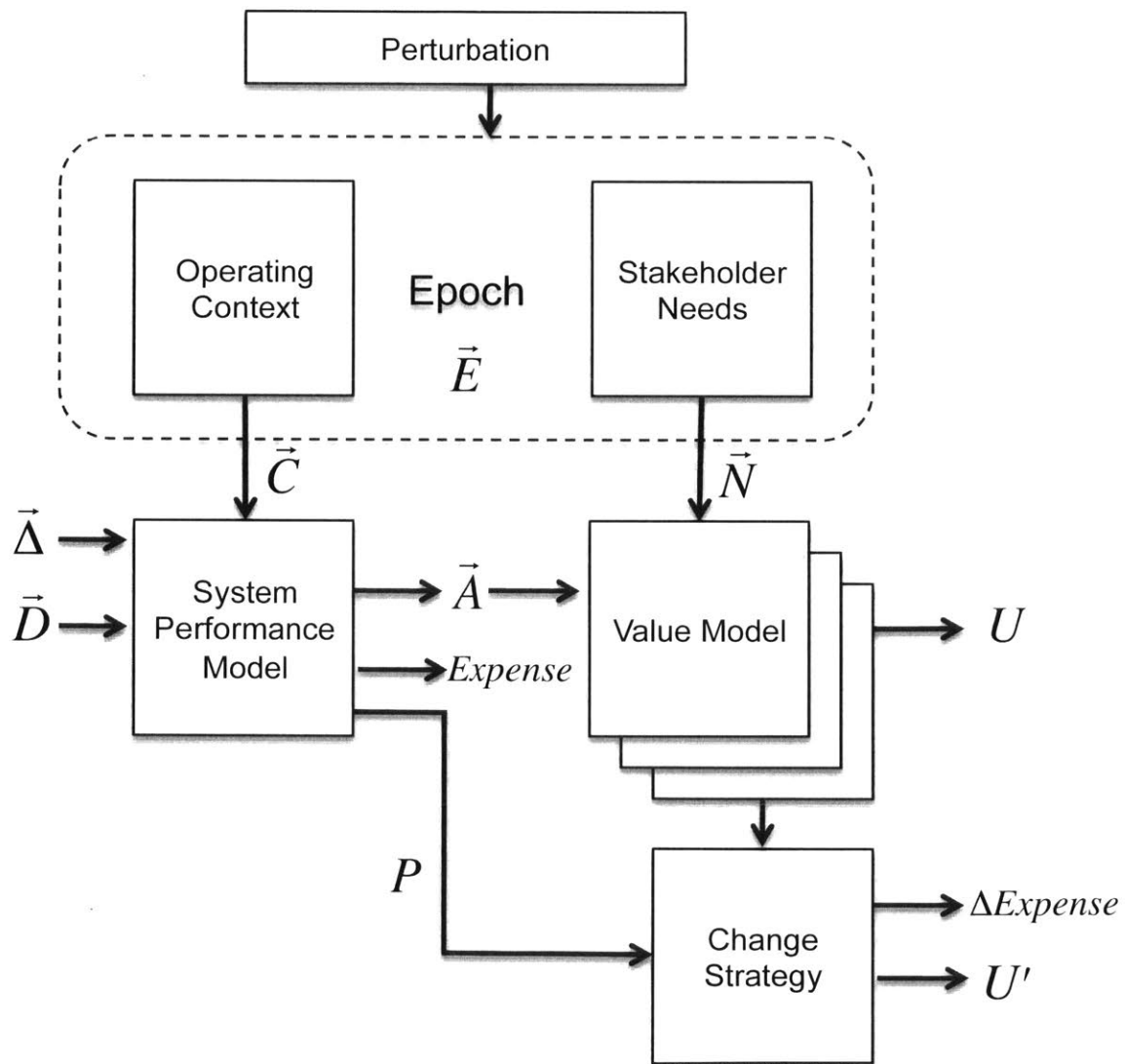


Figure 4-1: Combinations of Design-Epoch-Era evaluated through performance, value, context and strategy models

1. Design vectors (D)

Design variables are used to decompose the system definition into descriptive variables. Typically, for each design variable, several discrete levels are defined that the designer is interested in evaluating. A particular instantiation of the all the design variables is a design vector (**D**) that describes a unique configuration of the system being analyzed. Multiple design vectors are often enumerated using an experimental design (typically a factorial design) as part of a study. This implies that the number of unique design vectors enumerated is the product of the numbers of level of each design variable which can be a large number.

2. Change options

Transitions from one design form to another design form can be accomplished through change options. These are features that are built into the design at some expense and then executed at some point in the future possibly at an additional expense. A change option (**Δ**) describes a transition from the current values of the design variables to a new set of target values and thus a new instantiation of the design vector (**D**). The change option may be dependent on the context (**C**) and include associated information about the expense that must be consumed to make the transition.

3. Performance attribute vectors (A)

Performance attributes are measures the individual characteristics of performance. A vector of the attributes (**A**) that describe the performance of the system as a whole are the outputs of a system performance model. The context vector (**C**) also influences system performance. Each pair or combination of design vector (**D**) and context vector (**C**) will have a corresponding performance vector (**A**).

4. Expense

Some literature considers the cost or expense of a design as simply another output of the performance model. However, given the amount of attention given to cost modeling as a separate discipline in the literature, it is called out specifically here for further discussion. The expense of a system can include all the monetary costs associated with it including its acquisition cost, operating cost and any costs associated with the execution of change options. More generally, an expense can be anything that represents a limiting resource. Time is one variable that is frequently considered an expense, but labor, raw materials or any other scarce asset could also be considered. This was discussed in some detail by Schaffner [29] who proposed aggregating all of these variables into a single multi-attribute expense (MAE) value for each design.

5. Context variables

The context in which a system operates influences its performance attributes. Context variables are defined in a manner similar to that of design variables. The key difference being that context variables represent exogenous factors outside the designer's control. Context variables and levels are enumerated in a way similar to that of design variables. Again, this is frequently done by computing a full-factorial enumeration, but could be enumerated in an alternative way at the discretion of the analyst. A unique instantiation of the context variables forms the context vector (**C**). Each pair of context vector and needs vector instantiations defines a unique epoch.

6. Value Models (e.g. Benefit) and Needs Vectors

A value model defines the mapping of performance attributes to a perceived value (**U**) of a given system. As used throughout this thesis, the value (**U**) is computed using a multi-attribute utility (**MAU**) function. Each **MAU** function may be comprised of several single-attribute utility (**SAU**) functions that correspond to the stakeholders' descriptions of preferences for each performance attribute. Each **SAU** function defines a mapping from the performance attribute level to a **SAU** quantity. The linear weighted sum of the **SAU** quantities is the **MAU** or perceived value (**U**) of the system. The needs vector (**N**) for a given stakeholder must therefore include both a description of the individual **SAU** mappings and their weightings. Each pair of context vector and needs vector instantiations defines a unique epoch. Note that while it is assumed throughout this thesis that utility theory is used to describe the value model of the system this is not strictly required. Alternative value models are likely feasible though not demonstrated here.

7. Perturbations

Perturbations are defined in this thesis using essentially the same definition used previously by Schaffner [29]. Perturbations are not variables, but rather a set (**P**) of operators or rules that can impact some of the other variables described. Each element of the set (**P**) describes a rule that is either a short-term (disturbance) or long-term (epoch shift) impact. These rules can result in updates to the design or context variables as well as inputs that alter the performance or value models.

4.3 Framework for Interactive Epoch Era Analysis (IEEA)

IEEA leverages human-in-the-loop (**HIL**) interaction to manage challenges associated with the large amounts of data potentially generated in a study, as well as to improve sense-making of the results. By allowing the structured evaluation and visualization of many design alternatives across many different futures and potential lifecycle paths, this new approach enables the design of systems that can deliver sustained value under uncertainty.

4.3.1 Extension of Prior EEA-based Methods

The framework described in this thesis is based on prior research on methods and processes for applying EEA constructs. The Responsive Systems Comparison (RSC) method, proposed by Ross et al. [45,46] as a prescriptive method for applying MATE and EEA, was developed to study system value sustainment through changeability. More recently, Schaffner [29] proposed the RSC-based Method for Affordable Concept Selection (RMACS) that expands the original seven processes of RSC to nine and explored the application of multi-attribute expense (MAE) to more effectively capture all resources expenditures required to realize a given system.

IEEA differs from both RSC and RMACS in that it strongly emphasizes iteration and human-in-the-loop (HIL) interaction throughout the process. Iteration is necessary because the analysis is inherently exploratory in nature. HIL interaction is necessary because the problem is not strictly deterministic or necessarily intended as a reliable prediction of system performance or future events. Often, there is both uncertainty and the potential for errors in assumptions or model implementation. This necessitates human judgment to make sense of the data, therefore this is not by its nature a problem that can be handed over completely to an automated optimization algorithm. However, some level of automated analysis could be beneficial as an aid to the user.

4.3.2 Description of IEEA Framework Modules

The purpose of IEEA, much like the purpose of RSC as described by Ross et al. [129], is to “guide the...practitioner through the steps of determining how a system will deliver value, brainstorming solution concepts, identifying variances in contexts and needs (epochs) that may alter the perceived value delivered by the system concepts, evaluating key system trade-offs across varying epochs (eras) to be encountered by the system, and lastly developing strategies for how a designer might develop and transition a particular system concept through and in response to these varying epochs”. To that end, as shown in Figure 4-2, the IEEA framework is characterized by 10 individual processes that can be abstracted into six main modules:

1. **Elicitation** of relevant epoch and design variables (often through interview).
2. **Generation** of all epochs, eras and design tradespaces (often including enumeration).
3. **Sampling** of epochs and eras in which to evaluate design choices.
4. **Evaluation** of designs in sampled subset of epochs and eras.
5. **Analyses** of design choices in the previously evaluated epochs and eras.
6. **Decisions** of final designs based on iterative evidence from previous modules.

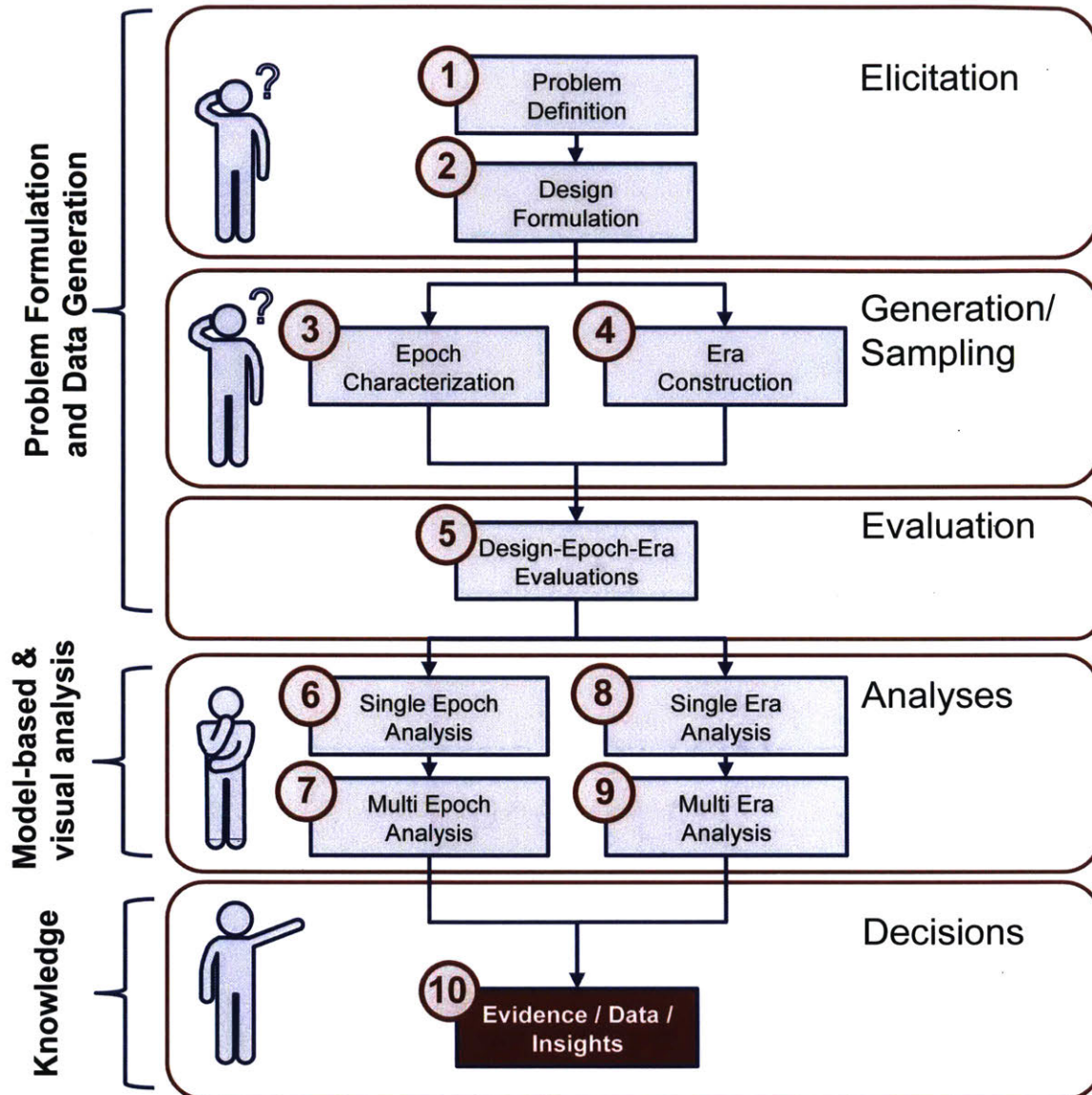


Figure 4-2: Interactive Epoch-Era Analysis process and modules.

This modularized approach provides consideration for implementation as well as multiple iterative and non-sequential workflows that are possible among the process steps. While the sequence of these modules flows logically, IEEA is intended to be an iterative process where users can go back and change responses within earlier modules at any point to reflect what they have learned from later ones. The six modules are composed of the 10 processes, but depending on the nature of the study and the type and fidelity of information available to the analyst, it is not strictly required that each process step be applied.

4.3.3 Description of IEEA Framework Processes

Visual analytics applications in other domains have shown promise for solving problems whose size, complexity, and need for closely coupled human and machine analysis may make them otherwise intractable [12,47]. A primary focus of research on the IEEA framework has been towards the development of visual analytics applications that can be applied to evaluate and demonstrate how enhanced human interaction techniques and visualizations can aid in the analyses and sense-making of high-dimensional multivariate EEA data sets.

The exact visualization and interaction approaches for implementing each of the process steps are non-unique and various issues can arise depending on the specific way in which a visual analytics application is implemented. For example, the specific software implementation of an interactive visualization application requires trade-offs in development effort, extensibility, comprehensibility, scalability and interaction latency. The exact visualization or analysis that is most useful to an analyst applying the IEEA framework is largely case-dependent. Therefore, the prototype visualizations developed for this research are not intended as a one-size-fits-all application, but rather as examples that demonstrate techniques and interactive visualization types that can be customized for a specific case.

Many of the techniques discussed in Curry et al. [127,128] can be applied to facilitate a practical implementation of IEEA. For example, online analytical processing (OLAP) techniques can be applied to improve data handling which enables scalability to larger data sets with more designs, epochs or other data dimensions. Interaction latency is a common issue as the size of the data set grows and prior research has shown that increasing latency can adversely affect user performance in exploratory data analysis [130]. This is largely task dependent, however, so a user-centric approach is recommended rather than focusing on reducing latency across all analysis stages. For operations that are sensitive to latency, such as brushing and linking between coordinated views, methods such as caching, pre-computing and pre-fetching can be applied to minimize latency. Trade-offs must be considered though, because it is not always beneficial or possible to pre-compute every conceivable piece of data that the user might be interested in evaluating.

Each process of the IEEA framework, with brief description of the activities involved which are adapted from prior work on RSC [45,46] and RMACS [29], is now listed:

Process 1: Value-Driving Context Definition (Problem Definition)

The first process of the IEEA framework is to identify the overall problem that the system is intended to solve, why it's important, and who cares about the problem and solution. This requires the identification of important stakeholders, the resources available to them to solve the problem, and relevant exogenous uncertainties. Relevant exogenous uncertainties include those key contextual factors outside the system

designer's control that may affect the problem or solution. The initial value proposition that describes how the system delivers value to the stakeholders should also be formed.

Process 2: Value-Driven Design Formulation

In this process, the need and resource statements for each stakeholder as expressed by their individual objectives are defined. From the needs statements key system performance attributes (metrics) and multi-attribute utility (MAU) functions describing each stakeholder's preference for those attributes can be identified. From the resource statements expense attributes and corresponding multi-attribute expense (MAE) functions can be identified. Frequently, the only expense considered is the lifecycle cost of the system alternatives, but other expenses such as scarce materials, labor or time resources may also be considered. Finally, system solution concepts should be proposed based on past concepts or opinions from subject matter experts (SME). These concepts are then decomposed into the design variables of the system.

Process 3: Epoch Characterization

In the third process, uncertainties in context and needs are parameterized. These will be the epoch variables that are enumerated in process 5 to describe various possible future contexts and needs that may prevent system value delivery in spite of the designer's intentions. These future contexts or needs may also enable value delivery if favorable conditions arise. Uncertainties in stakeholder resource availability and usage preferences are also identified.

Process 4: Era Construction

This process constructs era timelines composed of multiple sequences of epochs with a set duration to create long-run descriptions of possible future scenarios a system may encounter. The activities in this process are in many ways analogous to those used in narrative or computational scenario planning. The future timelines can be constructed manually with the aid of expert opinion (narrative) or by implementing probabilistic models (computational), such as Monte Carlo simulation or Markov chain models, that define epoch transitions.

Process 5: Design-Epoch Evaluation

This process begins by enumerating discrete levels of design and epoch variables that can then be mapped to the performance and expense attributes of the system utilizing modeling and simulation. Stakeholders' utility and expense functions are then used to generate the MAU and the MAE for each design, within each epoch.

Process 6: Single Epoch Analyses

This process includes the analysis of benefits and costs (expenses) of alternatives within particular epochs. Though several acceptable valuation approaches exist (e.g. AHP, NPV, QFD) the most-commonly used are MAU vs. MAE. Frequently this process involves the graphical comparison of feasible design alternatives (those that are within required performance bounds) using a scatter plot of MAU vs. MAE for any given epoch (time period of fixed operating context and stakeholder needs). The goal then is to identify so-called Pareto-efficient designs that provide the most benefit for a given

expense. Other within-epoch metrics, such as yield (percent of all designs that are feasible), give an indication of the difficulty of a particular context and needs set for considered designs.

Process 7: Multi-Epoch Analysis

This process seeks to identify designs that value robust across changing contexts and needs by implementing short run passive and active strategies for value sustainment. After completing the traditional tradespace exploration activities of Process 6, in which the analyst compares potential designs within individual epochs, metrics are derived from measuring design properties across multiple (or all) epochs to provide insight into the impact of uncertainties on design candidates. In addition, resource usage can be analyzed to identify designs that are robust to the expense factors identified in Process 3 (e.g. decreasing budgets or labor availability).

Process 8: Single-Era Analyses

This process performs lifecycle path analysis to examine the impact of time-dependent uncertainties described by era timelines that are composed of unfolding sequences of future epochs that were created in process 4. By examining a particular series of epochs for a given length of time, decision-makers can identify potential strengths and weaknesses of a design and better understand the potential impact of path-dependent, long run strategies for value sustainment.

Process 9: Multi-Era Analysis

This process extends Process 8 by evaluating the dynamic properties of a system across many possible future eras, identifying patterns of strategies that enable value sustainment across uncertain long run scenarios.

Process 10: Presentation and Knowledge Capture

Decide on final design choices based on data generated and analyzed during previous processes. The purpose of this process is to capture not only the final decision that is made, but also the chain of evidence that led to that decision which can also be captured in a database or by some other knowledge management system. This information may prove useful to future studies by allowing the analysis of the rationale and specific assumptions that went into a decision.

4.4 Implementation of a Visual Analytics Application for IEEA

The IEEA framework as a whole utilizes many of the data management capabilities discussed in Chapter 3. Process 2, design formulation, and the processes of the analysis module (processes 6 through 9) also derive significant benefits from the implementation of customized interactive visualization. It is also possible that the generation and sampling processes (3 and 4) could benefit from implementation in an interactive application by helping an analyst or decision-maker better articulate their design problem, but these are not yet implemented. The specific interactive applications developed as part of this research are discussed in the following subsections.

4.4.1 Process 2: Value-Driven Design Formulation

Recall the description of this process from section 4.3.3:

In this process, the need and resource statements for each stakeholder as expressed by their individual objectives are defined. From the needs statements key system performance attributes (metrics) and multi-attribute utility (MAU) functions describing each stakeholder's preference for those attributes can be identified. From the resource statements expense attributes and corresponding multi-attribute expense (MAE) functions can be identified. Frequently, the only expense considered is the lifecycle cost of the system alternatives, but other expenses such as scarce materials, labor or time resources may also be considered. Finally, system solution concepts should be proposed based on past concepts or opinions from subject matter experts (SME). These concepts are then decomposed into the design variables of the system.

A key objective of this process is for the stakeholder(s) to clearly articulate their preferences for the individual performance attributes associated with the available design alternatives. Often this is done speculatively and a stakeholder will want to revise their weightings and mappings of single attribute utility (SAU) functions after they better understand their impact on the tradespace as a whole. The interactive application shown in Figure 4-3 was developed to assist in this process.

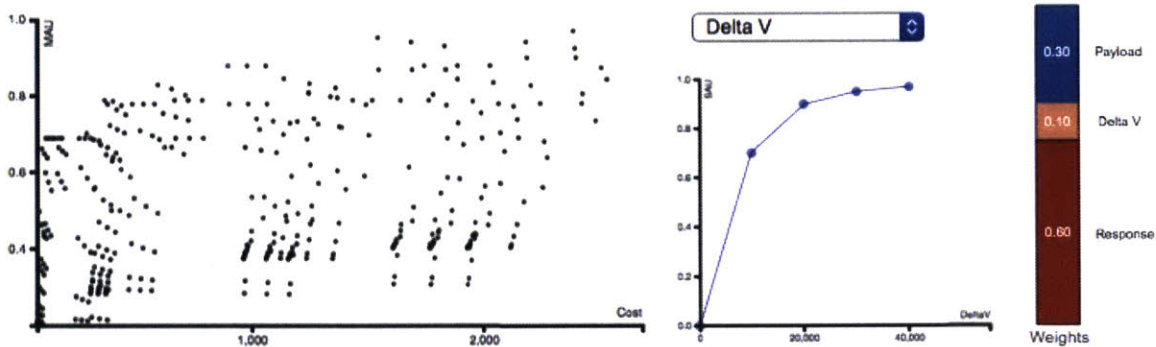


Figure 4-3: Value-mapping interactive application

The visualization provides an overview of the tradespace in a cost versus MAU scatter plot of the design alternatives. The shape of the curve that shows the mapping of one of the associated performance attributes and its mapping to an SAU function is shown to the right of the main scatter. To avoid chart clutter for case studies that have large numbers of performance attributes only one SAU curve is displayed at any given time. The dropdown menu allows the analyst to select any of the other performance attributes that contribute to MAU to update the display.

In addition to the dropdown menu an analyst can also interact with the chart in several other ways. To change the shape of SAU curve the markers on the chart can be

clicked and dragged to a new position. The shape of the curve is constrained to be monotonically increasing. The analyst can also change the weightings of the SAU functions. To do so, they can click on the text of the stacked bar to bring up a context menu which allows a new value between 0 and 1 to be entered. For this implementation, the total weight is constrained to equal one.

To access details on demand the analyst can hover the mouse over any point in the main scatter plot as shown in Figure 4-4. The point will increase slightly in radius and bring up a tooltip with additional information about the x-y position of the data while the mouse is hovered over it. In the coordinated SAU chart a red dot is highlighted to show where that point maps for the selected performance attribute. This allows the analyst to gain a better feel for how adjustment to the shape of the SAU curve might impact particular points in the main scatter plot.

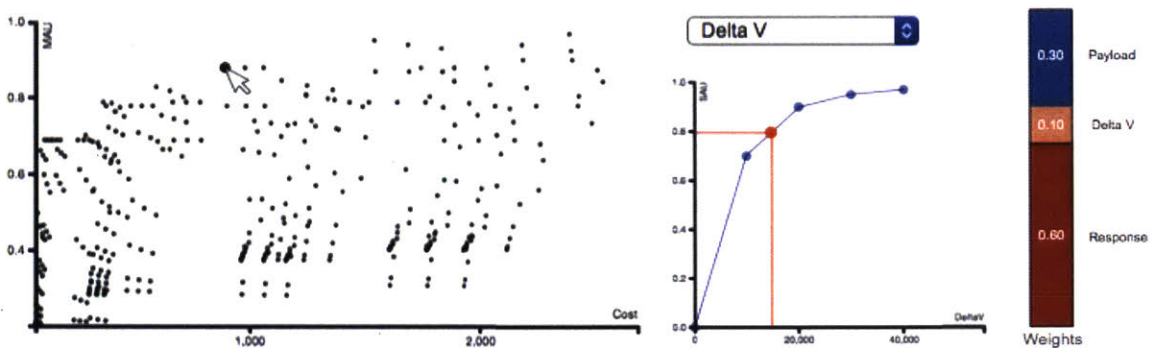


Figure 4-4: Interaction behavior for value mapping application

4.4.2 Process 6: Single Epoch Analyses

Recall the description of this process from section 4.3.3:

This process includes the analysis of benefits and costs (expenses) of alternatives within particular epochs. Though several acceptable valuation approaches exist (e.g. AHP, NPV, QFD) the most-commonly used are MAU vs. MAE. Frequently this process involves the graphical comparison of feasible design alternatives (those that are within required performance bounds) using a scatter plot of MAU vs. MAE for any given epoch (time period of fixed operating context and stakeholder needs). The goal then is to identify so-called Pareto-efficient designs that provide the most benefit for a given expense. Other within-epoch metrics, such as yield (percent of all designs that are feasible), give an indication of the difficulty of a particular context and needs set for considered designs.

As the process description states, in this analysis step an analyst typically wants to compare the benefits provided by a particular design alternative relative to the costs associated with it. For simplicity, it will be assumed in this section that we want to

compare designs for which we have evaluated MAU values that are a function of their performance attributes and MAE values that are comprised only of the cost to acquire the system. This is in line with a traditional tradespace exploration problem that is often graphically evaluated in practice using a scatter plot as shown in Figure 4-5. Scatter plots represent the data with circles shown on two common scales, the x and y-axis, which Cleveland and McGill determined to be the easiest perceptual task [101]. Additional data can be represented on the same visualization by encoding other data dimensions using color, shape or size of the points. Lewandowsky and Spence showed that altering color is the most discernable encoding to viewers followed by shape and size [131]. Text labeling can also be a useful possibility when the number of points is relatively small. This theoretically allows up to six dimensions (x, y, size, color, shape, label) to be displayed on a single scatter plot simultaneously.

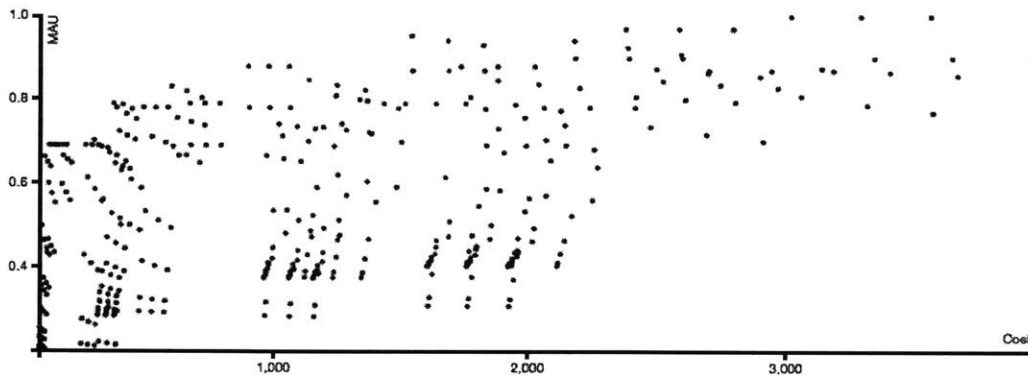


Figure 4-5: Example scatter plot of MAU vs Cost

As part of this process an analyst may also need to be able to look at the relationship between the interesting points observed in the MAU / MAE space and relate them back to their underlying performance attributes and design variables associated with them to identify patterns or correlations. Providing this type of overview may require the display of more data dimensions than are possible with a scatter plot. An alternative type of visualization that can display relationships between variables across more dimensions is a parallel coordinate chart as shown in Figure 4-6. This is a reasonable choice for this task because, of the visualization types evaluated by Harrison et al. [132], scatter plots and parallel coordinates were identified as the best for detecting correlations between data dimensions. Previously developed interactive applications have also demonstrated that combining parallel coordinates and scatter plots are a promising approach for analyzing complex data sets such as climate data [175]. Adopting a similar approach may also prove useful here.

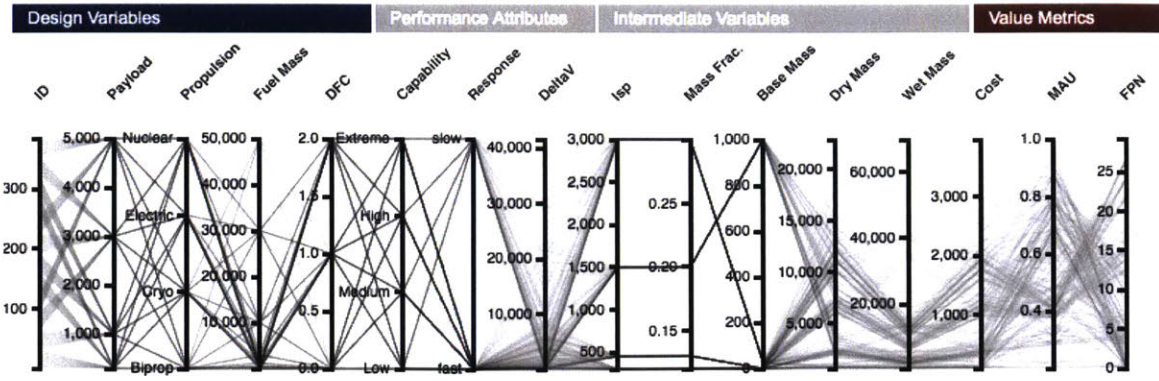


Figure 4-6: Parallel coordinate chart

Combining the scatter plot with the parallel coordinate view of the same data set to form a coordinate view with linked interactions is an even more powerful tool for an analyst. The combination of the views provides the “**Overview First**” part of the visual analysis mantra. Adding interaction enables the analyst to change their view or exclude data points from consideration using zooming and filtering operations thus providing the “**Zoom/Filter**” part of the mantra. Using brushing and linking as shown in Figure 4-7, an analyst can set criteria that will remove data points from both visualizations by dragging a bounding box along any of the dimensional axes of the parallel coordinates chart. The interactive application allows multiple filters to be set in this way so that only a subset of interest to the analyst remains visible.

An important consideration for any visual analytics application is its scalability to larger data sets. So far, the example shown in this section for demonstration purposes, and discussed in greater detail in Chapter 6, has only contained approximately 400 design alternatives. If the number of points on the scatter plot were significantly increased occlusion becomes an issue as points start to overlap one another. One option for overcoming this visualization issue is to incorporate a spatial binned aggregation strategy such as those described by Liu and Heer [65]. Rather than plot a dot for every single design rectangular or hexagonal bins, like those shown in Figure 4-8 for an example with approximately 15,000 data points, can be used to represent multiple points where the density of points within an area is encoded by color. This significantly reduces the number of visual elements that must be drawn on the screen which can improve readability and reduces latency when rendering and interacting with the visualization.

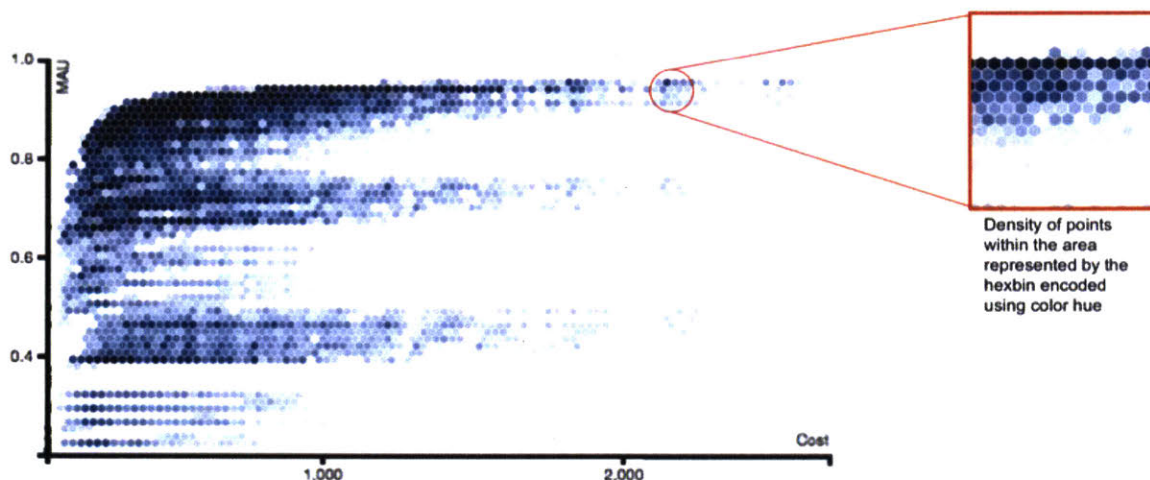


Figure 4-8: Dense scatter plot represented using hexbins

Similar issues with occlusion and clutter in parallel coordinate charts can occur as the size of the data set increases. For this application visualization issues are mitigated by reducing the opacity of lines that are not the current focus which makes the relevant lines more readable. However, this does not remove the elements entirely from the screen. If latency is an issue, an alternative approach could be to incorporate multiresolutional views such as hierarchical clustering or other techniques that can be used to reduce the number of elements that must be drawn on the screen to increase performance [133,134].

4.4.3 Process 7: Multi-Epoch Analysis

Recall the description of this process from section 4.3.3:

This process seeks to identify designs that value robust across changing contexts and needs by implementing short run passive and active strategies for value sustainment. After completing the traditional tradespace exploration activities of Process 6, in which the analyst compares potential designs within individual epochs, metrics are derived from measuring design properties across multiple (or all) epochs to provide insight into the impact of uncertainties on design candidates. In addition, resource usage can be analyzed to identify designs that are robust to the expense factors identified in Process 3 (e.g. decreasing budgets or labor availability).

There are some similarities between the types of analyses required by single-epoch and multi-epoch analysis, but there are also some key differences. First, since multi-epoch analysis requires the examination of how the same design alternatives perform and how their perceived value changes between epochs, there is generally a larger amount of data to consider. Secondly, whenever an analyst wants to examine changeability as a means for sustaining system value over time they must consider not only the original form of a design at the beginning of operation, but also the various forms it can take on through the execution of change options. To comprehend the impact this has on system value the analyst must be able to comprehend the impacts of both the cost and time it takes to execute a change option, its perceived value before and after changing, and the way operational strategies drive the use of change options.

Several interactive visualization applications have been developed for multi-epoch analysis as part of this research effort on IEEA that enable different ways of analyzing the problem. The first is an extended version of the single-epoch application that adds interaction in the form of a dropdown menu for switching the displayed data between epochs as shown in Figure 4-9 and Figure 4-10. This is a natural extension of the prior single-epoch application that has the advantage of keeping the interface consistent and familiar to an analyst. When the epoch is changed via the dropdown menu the points currently within the user-specified brush filter shift on the scatter plot based on their updated values in the new epoch. Animated transitions are used so that the analyst receives a visual cue as to how the data has changed. For cases where certain designs are no longer valid in the new epoch, these design points will be moved out of the current view. Interactive text above the design list table will also be updated to provide feedback on the number of remaining valid designs. If an analyst needs to follow a particular point or set of points through epoch shifts with greater scrutiny they can click on them to mark them with a tracking “halo” as shown in Figure 4-10. The halo will follow the design through epoch shifts to provide an additional visual cue to the analyst.

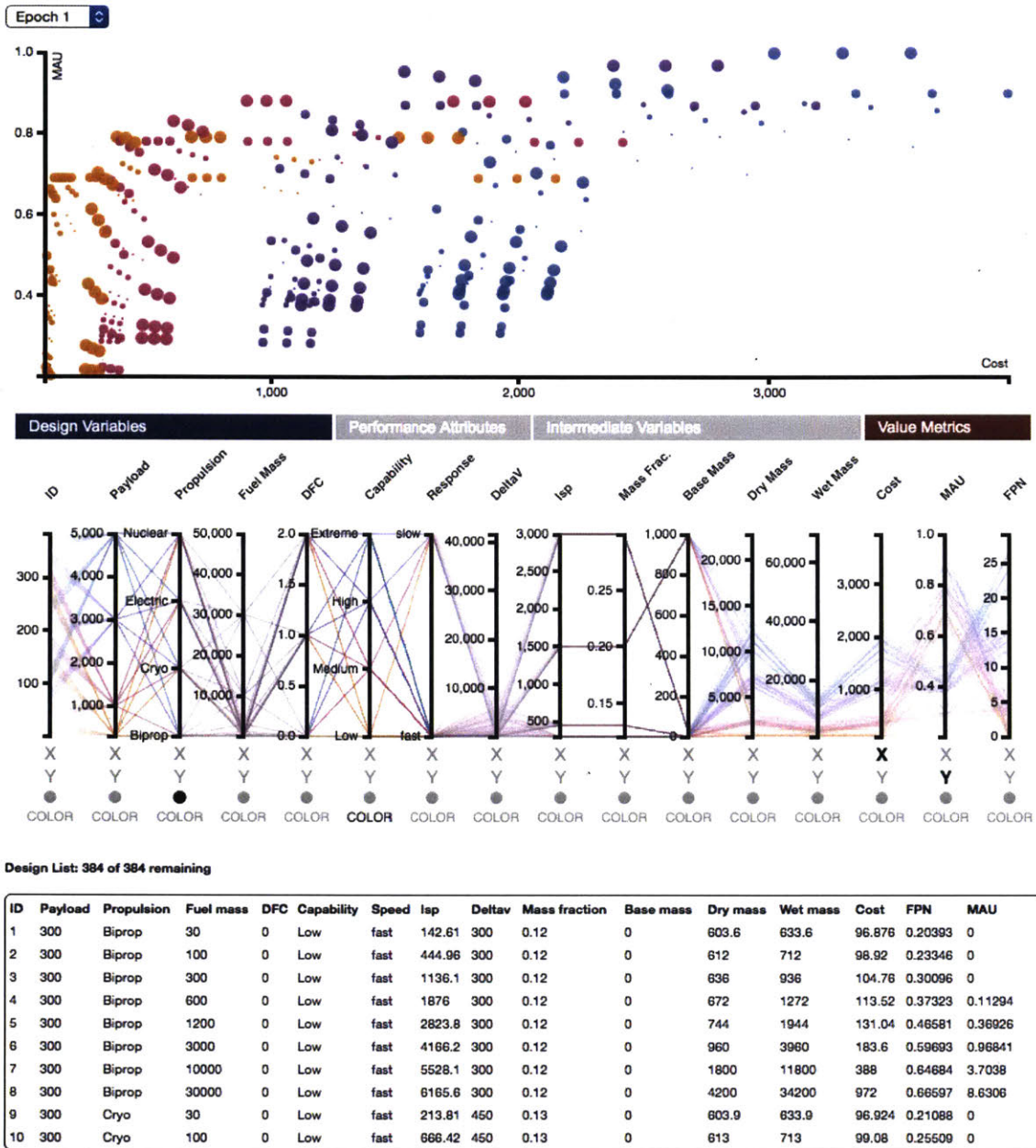


Figure 4-9: Single and Multi-epoch analysis visualization

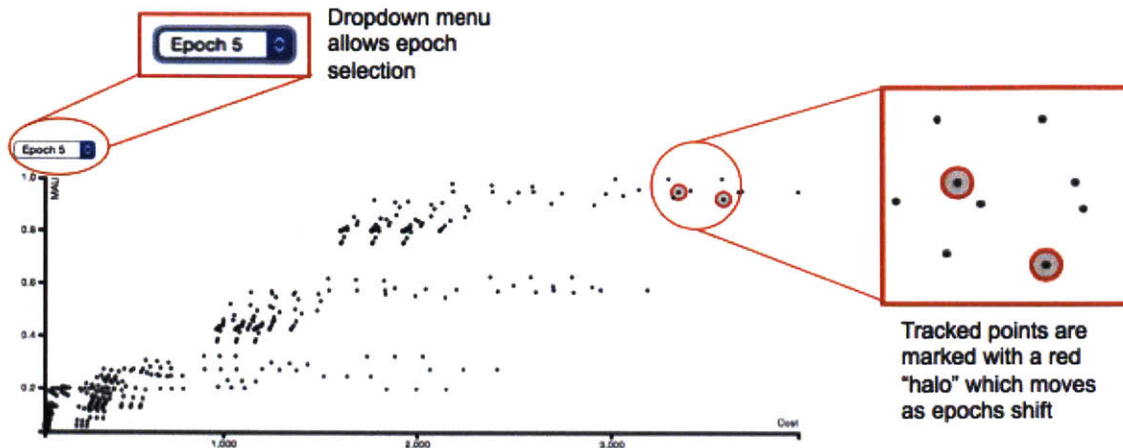
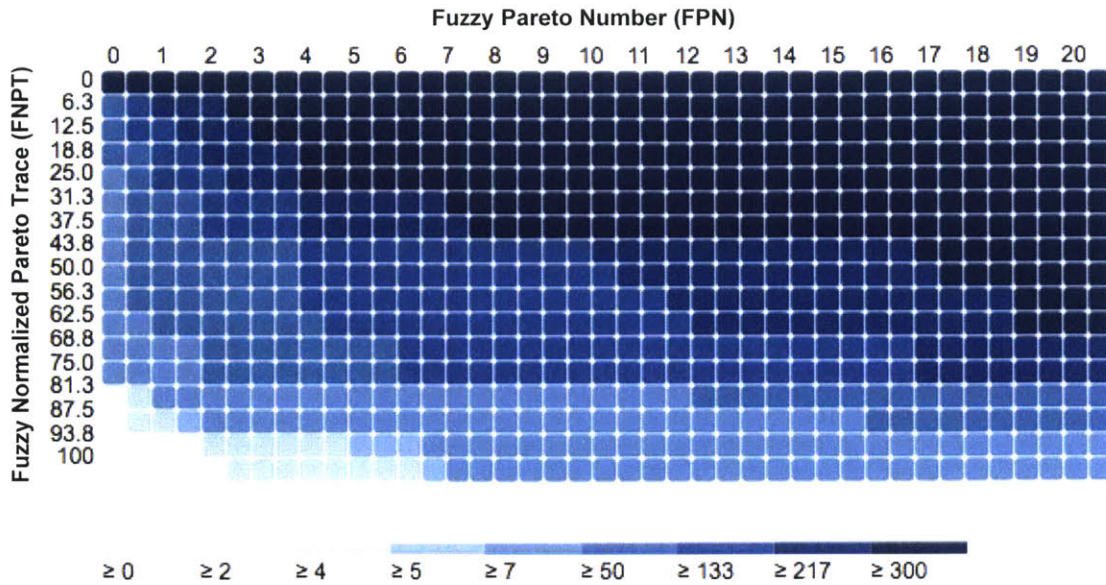


Figure 4-10: Epoch selection and point tracking in multi-epoch application

Extending the single-epoch application as described provides a convenient way to perform multi-epoch analysis, but does have some limitations. Because it only displays one epoch on the screen at a time it can be difficult for an analyst to compare large numbers of epochs due to the limitations of human working memory. The use of the dropdown menu for switching between epochs can also become cumbersome or impossible to use as the number of epochs increases. Lastly, the interactive application provides no direct way to assess the fuzzy normalized Pareto trace (fNPT) of a design to gauge its robustness across epochs.

To overcome these limitations an additional application was developed in the form of an interactive heatmap visualization. Two versions of this application are shown in Figure 4-11 and Figure 4-12, respectively. Both versions allow direct examination of the tradeoff between efficiency (FPN) and robustness across epochs. Robustness across epochs is assessed using the fNPT metric. In the first version, the grid of squares use color to encode the number of designs that satisfy a certain percentage of epochs at a particular “fuzziness” level. In this way, to find more acceptable design alternatives, an analyst can get a good overview of the relative merits of relaxing closeness to the Pareto front versus the number of satisfied epochs by examining the heatmap. Clicking on any of the squares in the heatmap provides details on demand in the form of a design list table which shows the designs that meet the analyst’s criteria. The second version of the heatmap provides similar functionality, but adds the capability for the analyst to assign an additional variable of interest to the size of the individual elements. In the example shown in Figure 4-12, the size element is assigned to a random number to demonstrate this functionality.



Of 384 designs 5 are within 1.0% (fPN) of Pareto optimal in 87.5% (fNPT) of enumerated epochs.

Design ID#	Cost	Capability	Engine Propellant	Fuel Mass (kg)	DFC
30	382	Low	Nuclear	3000	0
63	900	Medium	Nuclear	10000	0
95	1540	High	Nuclear	10000	0
128	3020	Extreme	Nuclear	30000	0
191	980	Medium	Nuclear	10000	1

Figure 4-11: Interactive heatmap visualization

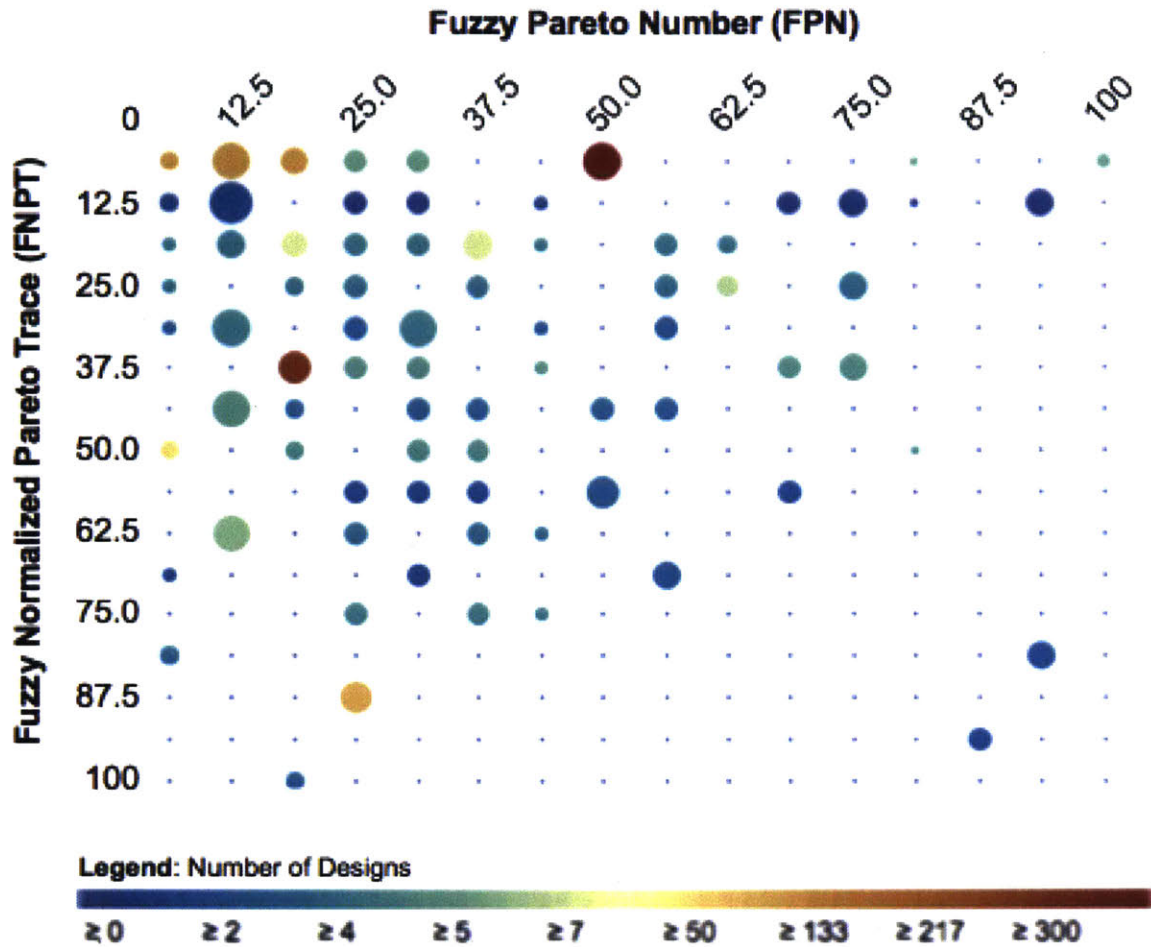


Figure 4-12: Interactive heatmap visualization with additional data encoded using size (Adapted from [135])

The heatmap visualizations provide a way to examine value sustainment across epochs through passive robustness. Another means for achieving value sustainment is through changeability. Allowing a design to execute design changes using options (e.g. real options) during their lifecycle gives them a way to change form in order to continue delivering value in the presence of evolving circumstances. An analyst may therefore want to identify designs that are not only passively robust, but also highly changeable. To evaluate a design's level of changeability a useful proxy metric proposed by Ross [27] is filtered outdegree (FOD), which represents the number of direct change paths out of a design to various target designs given a set of filtering constraints on resource usage such as execution time and expense (cost). If additional end states that can be reached through multiple change mechanisms are also considered, as suggested by Schaffner [29], this metric is referred to as the fully accessible filtered outdegree (FAFO). The various forms of outdegree are measures of one form of network centrality. Though outdegree is the type of centrality considered almost exclusively in past EEA studies, other centrality metrics, such as betweenness and closeness, may also serve as useful proxies for valuable changeability. Therefore, these centrality metrics are also incorporated into the research on IEEA.

Since the interactive heatmap visualizations are geared more towards examining passive robustness, new visualization types were developed to help the analyst better evaluate and make choices regarding design changeability. Though adjacency matrices have previously been used to visualize design change networks, interactive force directed graphs, as shown in Figure 4-13, might facilitate deeper insights from changeability analysis. This visualization follows the same pattern described by the visual analysis mantra: overview first, zoom/filter, details on demand. For instance, in the initial overview display the existence of communities of designs related to one another through change mechanisms is readily apparent even without applying clustering algorithms such as the Louvain community detection method.

Compared to the static adjacency matrix representations that have been used in prior EEA case studies, interactive visualization allows the represented network to be explored using dynamic data filtering and by changing the variable assignments of the visual elements. Using controls and filters that allow an analyst to assign node color, node radius, link width, link length, and link color to different data dimensions an analyst can more readily identify unexpected results. In the example shown in Figure 4-13 the visualization on the right shows the result from interactively assigning network centrality metrics for betweenness to both node color and radius. Doing so provides immediate visual feedback that designs, even within the same cluster, are not necessarily changeable in the same way in terms of available end states and costs to reach them. Hovering the mouse over the elements of the force directed graph provides details via an on demand tooltip for any of the nodes (designs) or edges (transition paths).

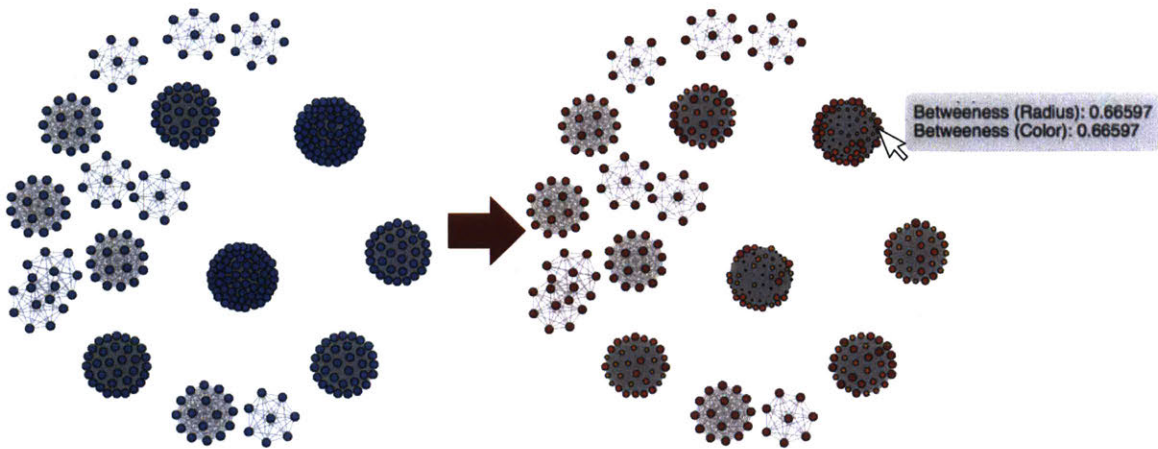


Figure 4-13: Interactive Force-directed graph

As the number of designs and change paths grow, directed graphs can quickly become cluttered and unreadable. They can also suffer from performance issues and interaction latency due to the large number of visual elements that must be rendered to the screen. Binned aggregation and OLAP techniques as discussed in Curry et al. [127] can be applied to overcome these types of issues. Pre-aggregating data dimensions and then rendering them as small multiples of binned histograms enables faster interactions

and filtering by reducing the amount of data that must be pulled into the browser's memory. It may also have benefits beyond just performance. Prior studies have shown that while visualizations with animated transitions tend to be rated highly for ease of use and enjoyment, visualizations that incorporate small multiples can be faster and less error prone for users working with large data sets [136]. The example application shown in Figure 4-14 incorporates both animated transitions and small multiples.

Consider a case where an analyst would like to concurrently examine the impact of various trades on eFPN, eFNPT and FOD metrics and how they impact design and performance variables with a data set that contains a large number of designs. The example interactive visualization shown in Figure 4-14 uses OLAP, multiple coordinated views and binned aggregation to allow fast filtering of design and performance variables as well as eFPN, eFNPT and FOD. This allows an analyst to quickly reduce the number of alternatives under consideration to a more manageable level and identify important patterns of behavior. This application also allows a decision-maker to determine not just the percentage of acceptable epochs, but also which epochs are most difficult for candidate designs. This is an insight not previously available or discussed in prior applications of multi-epoch analysis for this case study. These types of previously undiscovered relationships and patterns within the dataset may be useful for identifying "problem epochs" or when determining cases where it might be more appropriate to build a combination of systems to satisfy all possible future epochs.

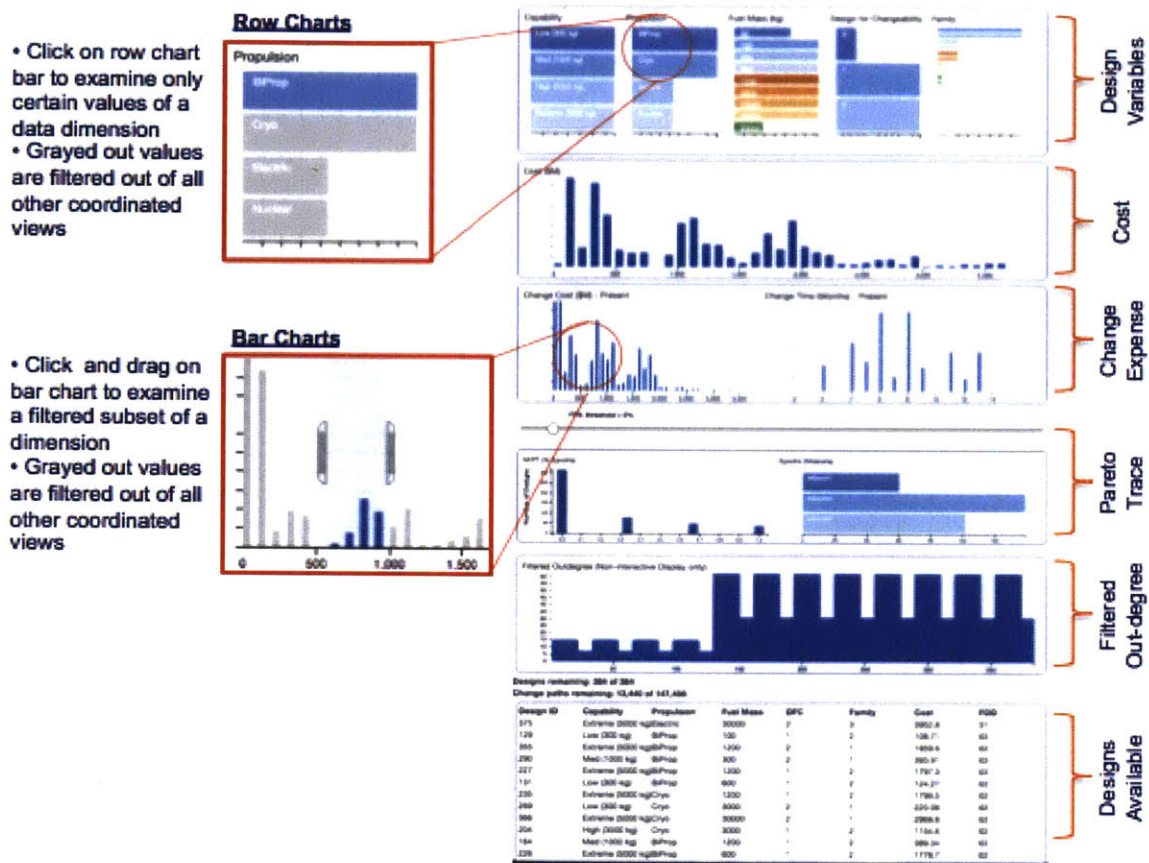


Figure 4-14: Multi-epoch analysis visualization using OLAP

A final consideration an analyst may need to make when performing multi-epoch analysis that has not yet been discussed is the selection of an operational strategy. For a system that has one or more change mechanisms, the decision as to which option to execute or whether an option should be executed at all depends on the strategy assumed. Fitzgerald [30] and Schaffner [29] describe several epoch-level change strategies that may be considered such as “maximize utility” or “maximize efficiency”. For the “maximize utility” strategy, as the name implies, it is assumed that a system will execute the change option or options that allow it to achieve the highest utility end state in a given epoch. Similarly, the “maximize efficiency” strategy will execute whichever options allow it to maximize Pareto efficiency and get closest to the Pareto front even if that results in a lower utility. The two authors also proposed other strategies, such as “Survive” and “Maximize Profit”, but it is possible that additional as yet undefined strategies may exist.

To better explore trades associated with different strategies and identify “problem” epochs, the interactive OLAP application shown in Figure 4-14 can be modified and extended. It would be tempting to assume that the Pareto trace section of the visualization identified in the figure above could just be replicated for the additional strategies that an analyst would like to consider. However, this would quickly become

cumbersome when many strategies are examined. It would also be problematic to add bars to the “inEpoch” bar chart if the number of epochs was large. Prior studies on human perception of proportions have shown that the effectiveness of bar charts decreases as the number of bars in the chart increase [137,138]. Those studies also suggest that pie charts are more effective at communicating proportions and more efficient with larger amounts of data as compared to bar charts. A visualization similar to a pie chart that may be useful here is an adaptation of Nightingale’s coxcomb (“rose”) diagram previously shown in Figure 3-10.

Shown in Figure 4-15, the adaptation of Nightingale’s coxcomb diagram provides compact visualization of the impact of alternative strategies on number of designs that satisfy a given epoch and their relative efficiency. For this example, the chart is divided into 16 equally-sized wedges, one for each enumerated epoch under consideration. Each wedge is filled in with two colors. The darker blue section represents a passive robustness strategy and the lighter blue representing a user selected strategy from the dropdown menu, in this case the maximize efficiency strategy. Each wedge section represents two important pieces of information. The radial length of the wedge section represents the percentage of the current design alternatives that have satisfactory performance in that epoch. The arc length of each wedge section provides a measure of the average proximity to the Pareto front of the current design alternatives. This is represented by percentage above the FPN threshold set by the user (e.g. $[1-e\text{FPN}]/[1-\text{FPN_threshold}]$). A fully filled in wedge would therefore show the analyst that all of the current design alternatives are Pareto optimal in that particular epoch. The benefit of this visual representation is that it gives the analyst a clear picture of not only which epochs are more difficult to satisfy, but also the gains they can expect by employing one strategy or another.

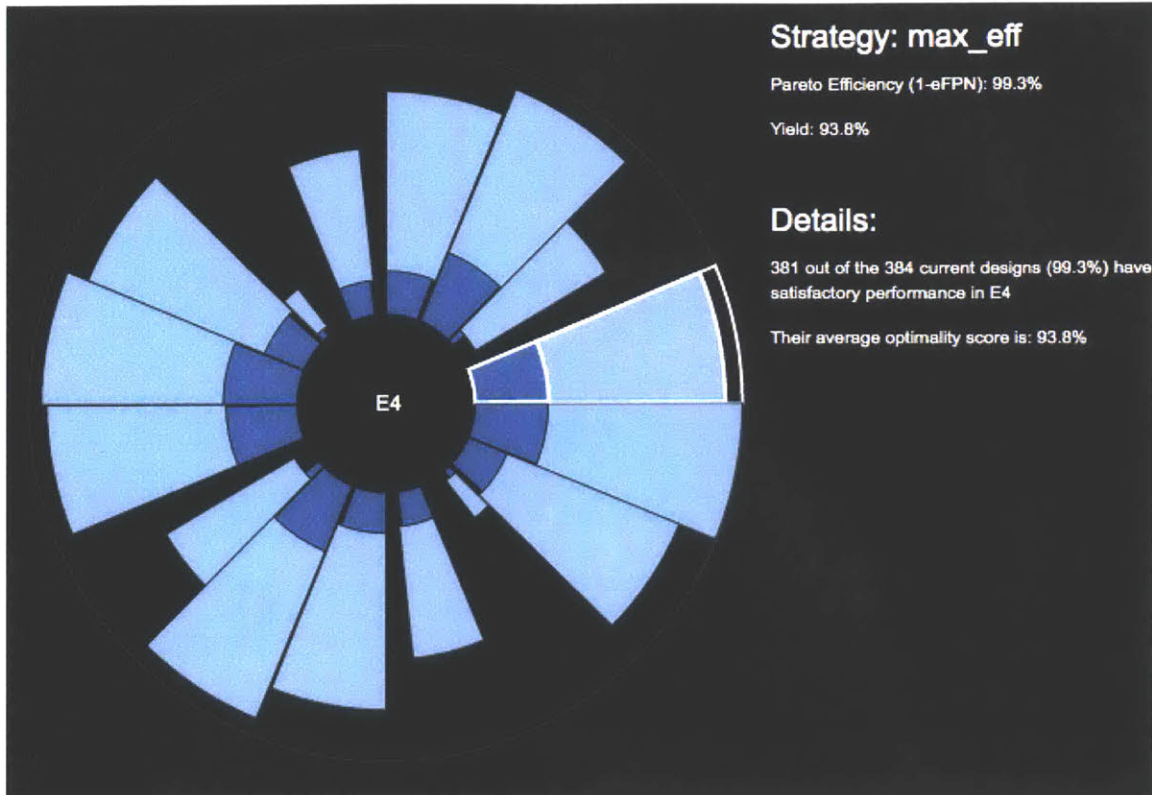


Figure 4-15: Nightingale coxcomb (“rose”) visualization

Incorporating the Nightingale coxcomb diagram as part of the larger OLAP-based visualization shown in Figure 4-16 provides a powerful extension over the original application shown in Figure 4-14. The chart as a whole provides the “overview first” by showing the distributions of design and performance variables as well as cost and various centrality metrics in addition to the information in the coxcomb diagram. The analyst can then filter the data along any dimension, change the acceptable FPN threshold, or select a new strategy and the chart will dynamically update. Details on demand are available by hovering the mouse over any element to get additional information in the form of interactive text to the right of the coxcomb as shown in Figure 4-15. The insights from this particular example will be discussed in greater detail for the case study described in Chapter 6.



Figure 4-16: Multi-epoch analysis OLAP visualization with Nightingale coxcomb diagram

Several interactive visualization applications have been discussed in this section for performing multi-epoch analysis. Each has their benefits and shortcomings so no single application should be viewed as a one-size-fits-all solution for this process step. Rather the applications described should be viewed as an ensemble of tools that can be applied to various problems depending on the particular needs of the case study.

4.4.4 Process 8: Single-Era Analysis

Recall the description of this process from section 4.3.3:

This process performs lifecycle path analysis to examine the impact of time-dependent uncertainties described by era timelines that are composed of unfolding sequences of future epochs that were created in process 4. By examining a particular series of epochs for a given length of time, decision-makers can identify potential strengths and weaknesses of a design and better understand the potential impact of path-dependent, long run strategies for value sustainment.

For many system design applications, subject matter experts may identify eras from one or more likely narratives that may play out. When analyzing any one of those eras a decision-maker would then want to identify the right combination of inherent robustness, changeability and operational strategy that allow a system to meet a specified performance threshold across all future time steps. As an example, assume a design is

desired to remain within a given distance of the Pareto front (e.g. FPN close to zero) across all time. A plot of the FPN versus time can reveal how each candidate design performs, but it is difficult to compare performance between designs across the era. Previous applications of era analysis [30,13] used variations of time-weighted average performance across an era to compare designs to one another. They also focused on utility, rather than FPN, as their metric of interest which is not necessarily appropriate since utility values are not comparable in different epochs. Schaffner [29] identified several additional metrics that can be applied to evaluate additional characteristics of performance across an era including expedience, variability, time-weighted average, greatest instant rise/fall, and range. These additional metrics provide an improved ability to describe era performance at the expensive of increased information that a decision-maker must consider when selecting a design.

As demonstrated for previous IEEE processes, decision-making in single-era analysis can also benefit from the application of techniques such as multiple coordinated views, interactive filtering and OLAP. An example application, shown in Figure 4-17, shows the FPN performance of all designs across time for the specified era. The five histograms to the right display aggregated data on the performance of the candidate design-strategy pairs for the era metrics identified by Schaffner [29]. Interactive filtering on those metrics allows a decision-maker to rapidly identify interesting designs based on their individual preferences for average performance and stability of performance across time. It also allows them a way to better comprehend design behavior that has not previously been demonstrated.

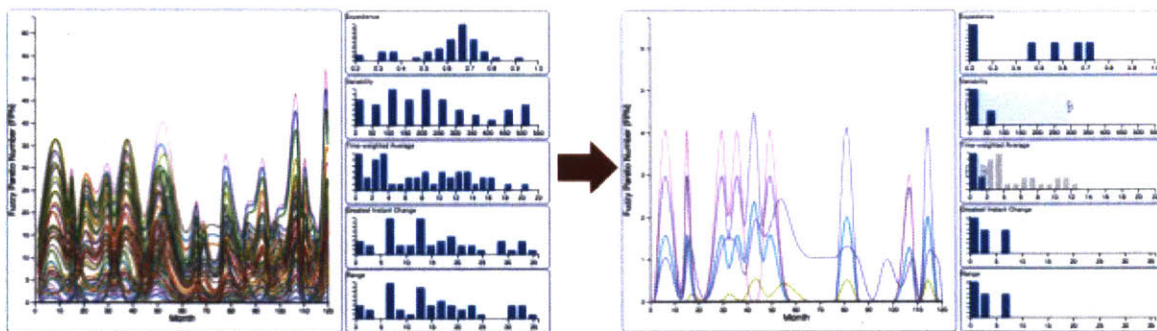


Figure 4-17: Single-era analysis visualization using OLAP showing (a) candidate designs before filter; (b) after filtering

Building on the application shown in Figure 4-17 a more sophisticated interactive visualization can be developed using multiple coordinated views and OLAP. Taken from a more detailed case study, the application shown in Figure 4-18 provides more visibility into the problem. In the case study two strategies are considered for six potential starting designs examined over six possible eras. This average and volatility of three measures of interest (FPN, MAU, and cash flow) can be interactively filtered to identify design-strategy pairs of interest to the analyst. Details on demand are available from the table on the right that can display additional information about a particular design-strategy pair in a given era.

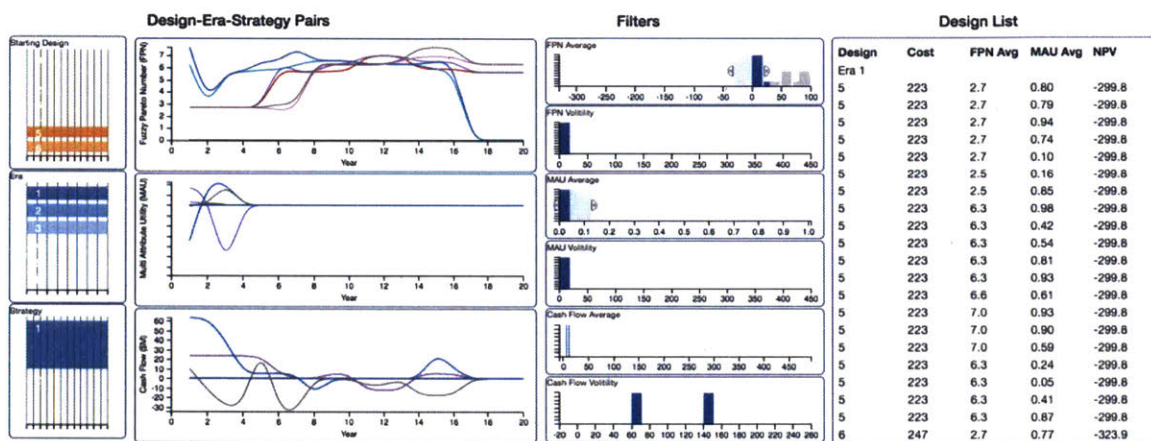


Figure 4-18: Single Era Analysis visualization using OLAP

4.4.5 Process 9: Multi-Era Analysis

Recall the description of this process from section 4.3.3:

This process extends Process 8 by evaluating the dynamic properties of a system across many possible future eras, identifying patterns of strategies that enable value sustainment across uncertain long run scenarios.

This process extends Process 8 by evaluating the dynamic properties of systems across many possible future eras, identifying patterns of strategies that enable value sustainment across uncertain long run scenarios. When looking at only a single or a small number of eras it is possible to compare how individual designs perform relative to one another using the era metrics previously discussed that capture temporal aspects of value delivery. This is not practical when analyzing many possible eras. In fact, it has been previously shown that it would be impossible to characterize the entire era-space [29,139]. The goal then for multi-era analysis is focused more on understanding the aggregate behavior of designs given different long-run strategies for operating a system. Specifically, it is useful to better understand any possible path dependencies that may arise due to either external perturbations/shifts or the application of operational strategies

that define usage rules for available design change options. The goal of identifying path dependencies is similar to that of other problems encountered in discrete combinatorial environments such as strategic games (e.g. backgammon, chess, go). Humans assisted by computing aids have shown some successful outcomes for tasks like chess [6] and path planning [140,141] in prior cases which suggests a similar coupling may be of value in system design problems with practically uncountable numbers of discrete outcomes.

Prior multi-era research [29] has examined the use of a parallel sets to visualize the proportion of design occurrences within the time duration of a particular epoch as shown in Figure 4-19. This type of visualization is useful in visualizing the temporal aspects of change across an era, but can become cumbersome for analysis across many long eras with many epochs. An alternative type of diagram that can be applied to this process is a chord diagram. Chord diagrams can be useful for comparing similarities or differences between elements in a group or to represents flows between elements. The example chord diagram in Figure 4-20 shows how nodes representing the groups are arranged around the circumference of a circle with connection or flows between those nodes drawn using arcs. Information can be encoded in the diagram using color and the proportionality of each node.

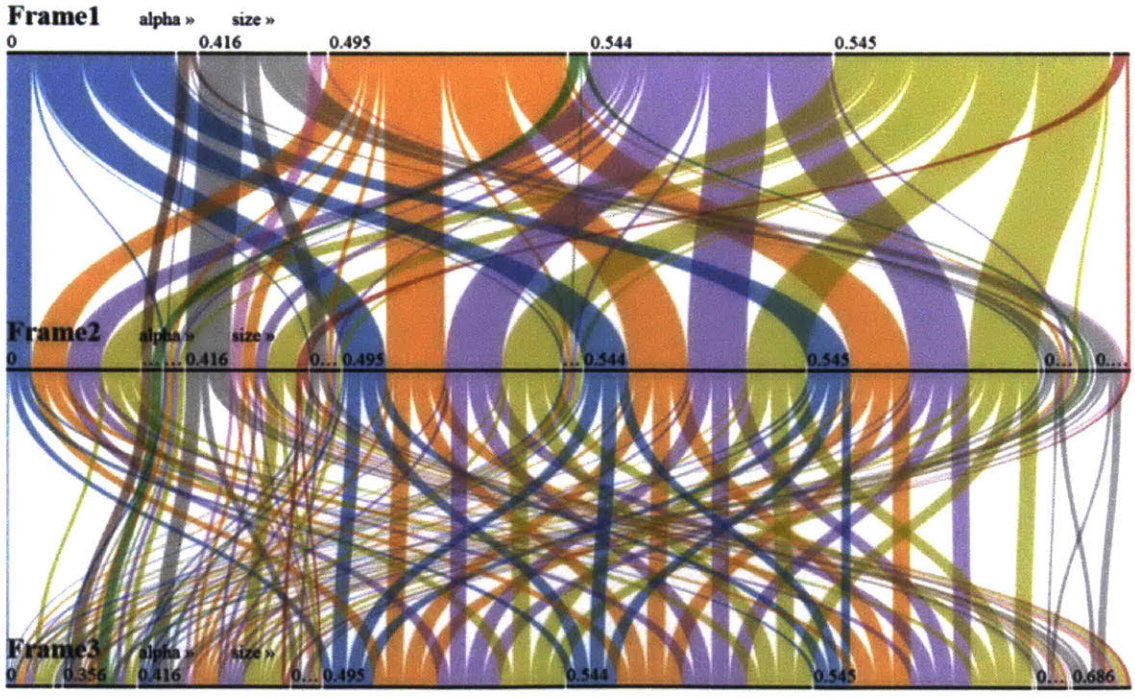


Figure 4-19: Visualization showing eras visualized using parallel sets[29]

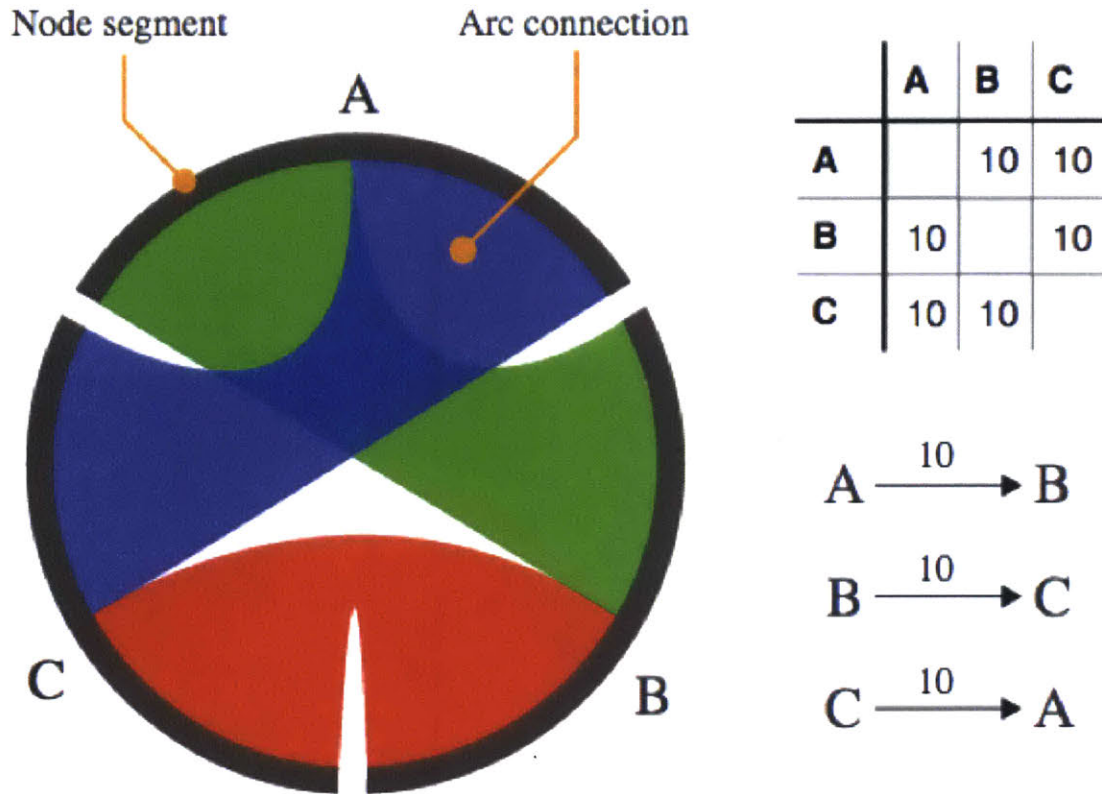


Figure 4-20: Example chord diagram

A new visualization, an interactive chord diagram, is introduced here as one possible way of representing aggregate change behavior in a more compact form. As shown in Figure 4-21, the chord diagram can be used to represent the proportion of the time that a source design executes a change option to reach various target designs across multiple eras. All the designs that use change options to sustain value are enumerated around the circumference of the diagram and quadratic Bézier curves show the proportion of each source design changing to each target. The source and target arcs represent mirrored subsets of aggregate change behavior.

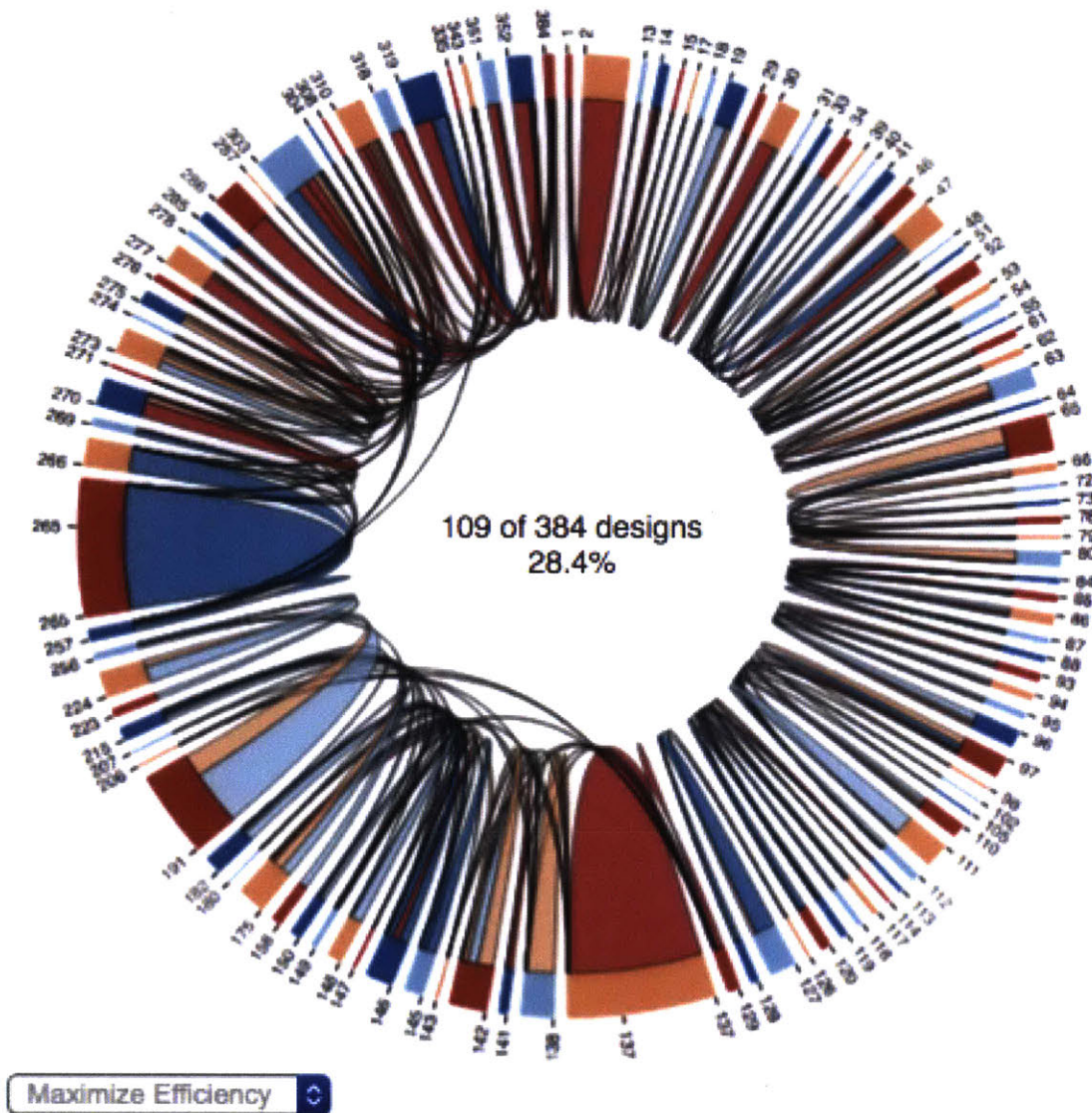


Figure 4-21: Interactive Chord Diagram

Because occlusion of overlapping curves can become an issue with chord diagrams when large numbers of nodes and connections are displayed, an interactive behavior is beneficial here. By hovering the mouse over a particular element in the visualization all other elements are removed from the current focus by reducing their opacity as shown in Figure 4-22. Interactive text is also displayed in the center of the chord diagram to give the analyst details on demand. Detailed analysis using this visualization allows an analyst to quickly identify designs that rely on changeability (rather than robustness) to maintain value and which options and end-state designs that are frequently used for various strategies.

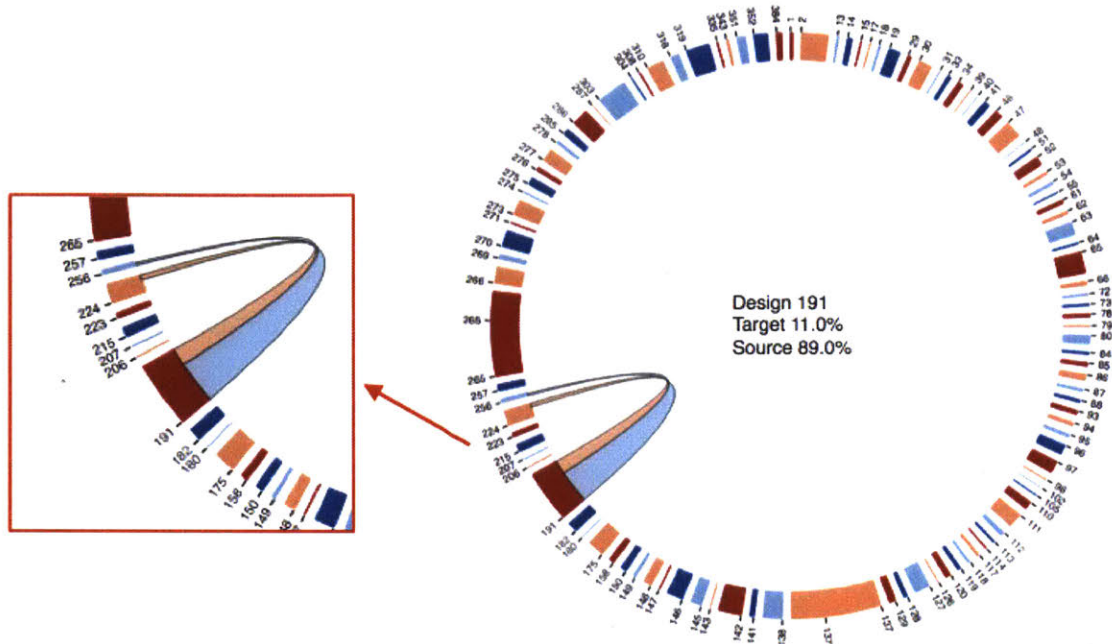


Figure 4-22: Chord diagram details on demand

As was the case with single-era analysis, this application could be extended further by incorporating OLAP and multiple coordinated views. The specific views of interest to an analyst would be dependent on the needs of the particular case study. Some examples that can be considered in later case studies are the addition of dimensional views for change cost, time and option used. As before, these dimensional views could be used to filter the data shown in the current display so that the analyst can reduce the alternatives under consideration to a manageable quantity.

5.0 Human Subjects Experiment on a Surrogate Design Problem

This chapter describes a controlled human subjects experiment designed to assess whether interactive visualization improves user performance for design problem tasks. A primary working hypotheses of this thesis research is that visual analytic applications that couple interactive visualization with design methods like EEA will provide a benefit to human performance. To that end, this experiment required subjects to answer questions related to a simplified engineering design problem equivalent to a multi-epoch analysis problem as described in Section 4.4.3. Subjects were randomly assigned to one of four treatment groups that were distinguished by the type of data representation or analysis tool they were given to solve the problem. It was anticipated that both the treatment group and individual differences between subjects impact performance as measured by task completion time, accuracy and cognitive load. Individual differences as discussed in this study refer to the subjects' measured personality traits and spatial reasoning ability. Results of the experiment confirm that this is indeed the case and that the way and degree to which human performance was affected varied by task type and data volume associated with the question.

5.1 Experiment Overview and Objectives

This experiment was designed to address one of the primary research questions of this thesis identified in Section 1.2:

RQ3: Does interactive visualization improve user performance for design problem tasks and, if so, what are the relative contributions of representation, interaction or other factor to user performance?

There are two components to this question that must be tested. First, is there any measurable impact on human performance when individuals are engaged in performing analysis tasks commonly associated with engineering system design problems? Second, can the degree to which an interactive capability, visualization or other factors, such as individual differences in the users, affect human performance be isolated and identified. For the purpose of this study human performance is measured in terms of the speed and accuracy with which a subject can complete a relevant task as well as their cognitive load while doing so.

A primary working hypothesis of this research is that interactive visualization will improve design task performance for some, or perhaps all, of these metrics, and visual representation and interaction with data used to complete the task will impact performance in different ways. To decouple the relative contributions of representation and interaction a 2-by-2 factorial experiment with a total of 4 treatment groups has been designed. Each treatment group corresponds to a different analytical tool that can be provided to test subjects to complete a design task. All subjects were randomly assigned to a treatment group and asked to perform analyses on a surrogate design problem,

comprised of several tasks. The surrogate design problem is a simplified version of a multi-epoch analysis problem. Because individual differences in personality or spatial reasoning ability may also play a role in task performance, data regarding these factors was also collected from participants using pre-test questionnaires.

A controlled human subjects experiment is an appropriate and effective approach for testing the working hypotheses. By controlling for whether or not a subject is given a data visualization and/or an interactive capability designed to aid them in solving a particular task, the factors most influential to performance can be isolated. While the individual differences of the subject volunteers cannot be controlled this experiment can still effectively measure the impact of these factors by collecting a large and diverse sample set of participants.

5.2 Subject Selection and Assignment

The participants in this study were drawn from volunteers using Amazon's Mechanical Turk (MTurk) online crowdsourcing marketplace. Crowdsourcing the evaluation of interactive data visualizations is an attractive option because of its convenience, ease of scalability to large numbers of participants, and relatively low cost. Previous research studies have assessed the viability and validity of using MTurk for these types of studies and provide guidance for its application [142]. Several other studies dealing with visualization and human performance have also shown that MTurk subjects can generate positive results [143,144,145,146].

Nearly any methodological technique presents some threat to external validity and crowdsourcing via MTurk is no exception. One common suggestion is that the quality of the work performed by MTurkers is low because many of them are willing to work for low wages and that effectively drives good workers out of the market [147]. Other researchers point out the potential for criticism because the test environment cannot be tightly controlled in online studies and the user may be distracted or participating in other task while performing the study [145]. Some of the guidance provided by Heer et al. [142] is useful for mitigating these concerns. For example, the use of qualification tasks to ensure subject understanding assignments and clearly worded tasks with verifiable answers can encourage volunteers to provide accurate results. Attention-check questions can also be inserted to verify that subjects are not distracted or randomly providing responses.

Another potential threat to validity that is sometimes suggested may result from using the Mturk platform is a relative homogeneous or non-representative sample population. However, research studies on the backgrounds of the MTurkers have shown that they are actually a fairly heterogeneous group of individuals from a wide range of industries and geographic locations and are diverse in terms of education, sex, age and race in ways that are similar to other professionally supplied samples [148]. This makes this cohort particularly useful in that it allows cross checking of results and possibly identification of unique characteristics that influence task performance. For instance, since subjects' individual differences are being examined in this study, there is more

likely to be a much wider range of characteristics in this cohort than more homogenous samples such as undergraduate students commonly used in social science studies. The extent to which students as research subjects creates a threat to validity is often recognized as a potential issue in academic research [149]. For example, the frequently cited work by Sears [150] refers to this type of group as a “narrow data base” which can constrain generalizability of results.

A final threat to validity that is considered is the possibility of the same individuals participating in the study multiple times. This is guarded against in two ways. First, the consent form seen by the Turkers on the first page of the experiment requires them to enter their unique Amazon worker ID. Turkers that entered an ID already associated with a completed test were not allowed to repeat it again. As an additional safeguard the originating IP address of Turker was also checked to verify that it did not match any previously submitted tests.

A total of 106 MTurk subjects were recruited for this study by posting a human intelligence task (HIT) task request on the MTurk requester website. Of the subjects that completed the study all but 2 successfully passed all attention checks and verification questions. The 2 subjects that did not pass attention checks were excluded from analysis thus there were 104 valid subjects in total. The HIT description seen by all participants prior to volunteering was identical regardless of the treatment group to which they would ultimately be assigned. As is the norm with the Amazon’s MTurk, a small reward was offered for volunteering to participate in the research study. Prior studies regarding MTurk visualization evaluations have shown that reward level has no significant impact on response quality, but do led to faster completion rates of a batch of HITs [142]. To be clear, this means that higher reward rates will result in the collection of data from more unique subjects faster over a given period, not that it will result in faster completion time for the HITs assigned task. For this experiment, to approximate a scale roughly equivalent to the U.S. federal minimum wage, subjects drawn from the MTurk cohort were compensated \$5.00 for their time.

5.3 Treatment Groups

The two primary controlled variables in this experiment were the presence or absence of (1) an abstracted representation of the data (e.g. chart, graph, visualization) and; (2) an interactive capability for manipulating or engaging with the data in some way (e.g. filtering, sorting). As discussed previously, it was hypothesized that these two things could aid a subjects understanding of a problem differently. To decouple the relative contributions of representation and interaction a 2-by-2 factorial experiment with a total of 4 treatment groups was designed. Each treatment group corresponds to a different analytical tool that is provided to test subjects to complete a design task. Figure 5-1 summarizes the four analytic tools subjects could receive as treatments in this experiment.

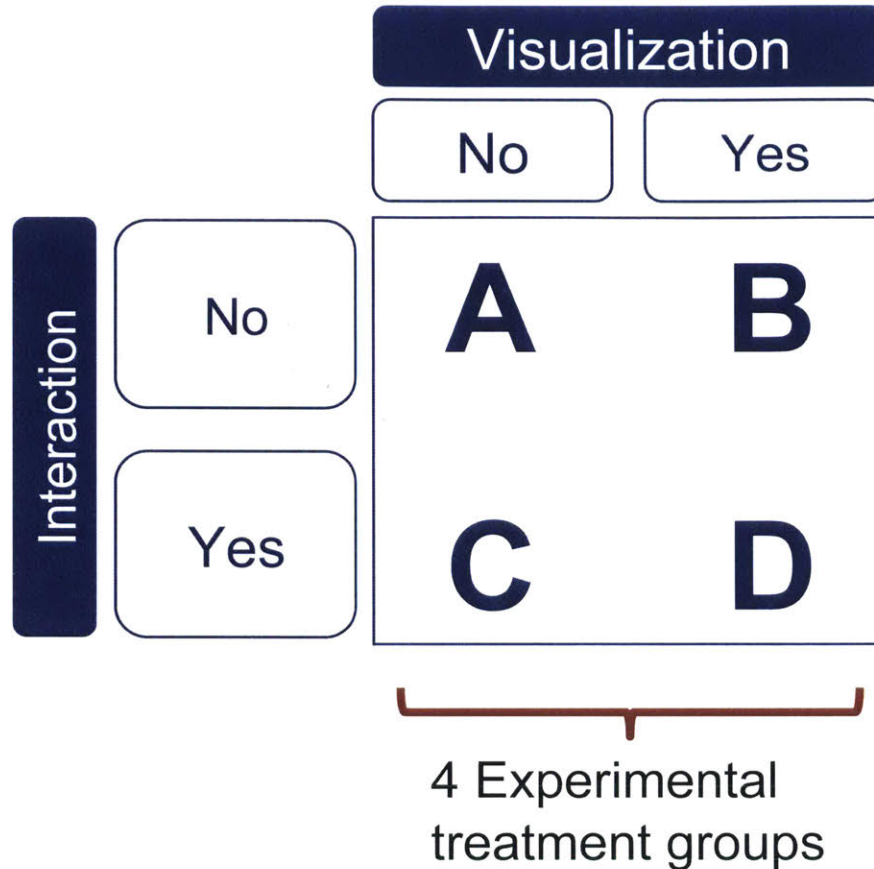


Figure 5-1: Experimental Treatment Groups

Subjects were randomly assigned to one of these four treatment groups, but each was given identical tasks and questions to answer. Careful considerations were given to ensure that none of the treatment groups were “handicapped” on the test in anyway. All of the task questions, which are provided in the appendix section 9.3, could be answered using the information available to subjects regardless of treatment group assignment. Each of the analysis interfaces was developed and implemented as a custom web-based interface using custom HTML, CSS and JavaScript as well as open source libraries, such as D3 [61], just like each of the actual interfaces described in Chapter 4. The subjects could use the interfaces to explore the data associated with the design problem to find answers to the task questions. Detailed descriptions of each of the four treatment groups are provided in the following sections.

5.3.1 Treatment A: Non-interactive Table

This group can be considered the control or standard treatment group in this study. As shown in Figure 5-2, subjects are given a non-interactive table on the screen that they must scroll through to determine the answer to task questions. Depending on the question, the list could contain up to 100 rows representing different design alternatives. To respond to questions participants must manually scroll through the list of

designs to find a piece of information or count the number designs that meet specified criteria. Subjects were not allowed to use offline post-processing tools to analyze the data. To prevent subjects from circumventing the test the copy and paste buffers on their web browsers are disabled at the beginning of the experiment.

design ID	cost	reliability	mpg	top speed	0% compromise	5% compromise	10% compromise	15% compromise	20% compromise
1	4200	77.1	22.2	89	0	1	2	3	3
2	4050	76.2	20.4	92	0	1	2	3	4
3	4250	79	23.3	88	0	1	2	3	3
4	3500	60	27	81	4	4	4	4	4
5	3550	67.6	17.2	88	2	4	4	4	4
6	3700	76.2	18.2	82	1	2	4	4	4

Figure 5-2: Treatment A – Non-interactive table

5.3.2 Treatment B: Non-interactive Table with Visualization

The interface provided to subjects that are assigned into treatment group B is an extended version of the one used for the control group. A non-interactive table identical to the one provided to group A is given to participants. In addition, a static graphical representation of the data is given in the form of a stacked and grouped bar chart that summarizes some of the key information from the table. The chart is designed to assist the user on questions that require identification of trends or patterns within the data. Figure 5-3 shows an example of what this combined interface looks like for an example test questions.

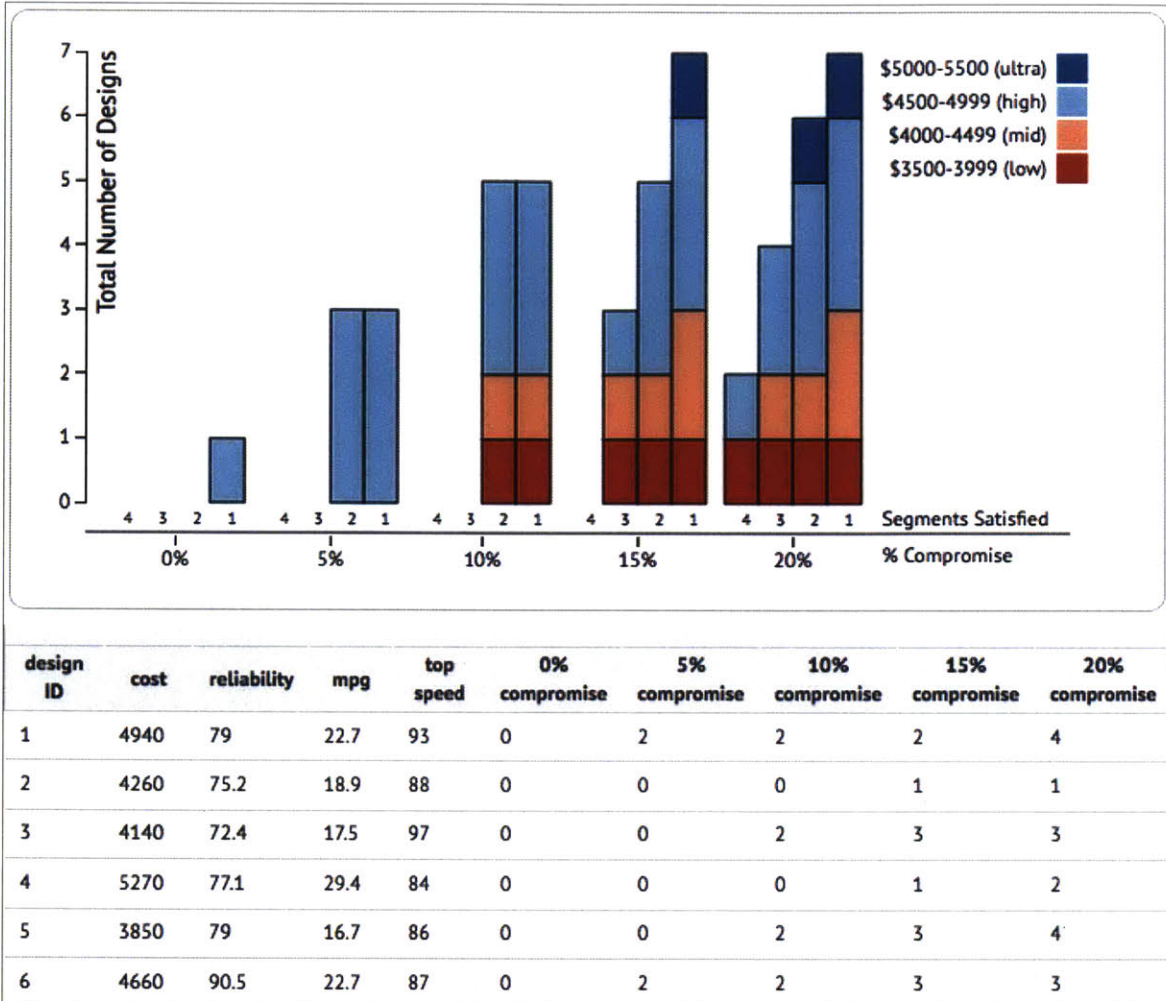


Figure 5-3: Treatment B – Non-interactive table with visualization

5.3.3 Treatment C: Interactive Table

The interface provided to subjects that are assigned into treatment group C is also an extended version of the one used for the control group. For participants in this group, rather than being given a visualization of the data, they are provided with an interactive capability that allows them to manipulate the data. The table itself is nearly identical in appearance to the table provided to group A participants with the exception of input boxes that appear above each of the column headers. The input boxes allow regular expressions such as “< 20” or “>= 3500” to be entered to filter the data set. When a filter is applied the table updates to show only the designs that meet the criteria specified by the user and the interactive text above the table indicates the designs remaining. Multiple criteria can be applied simultaneously to filter the data. In addition to filter interactions, users can also interact with the interface by clicking on column headers to sort the data in numerical order. Clicking once a particular column header sorts the data in ascending order using that data dimension. A second click on the same column header will sort the

data in descending order. These interactive features are designed to assist the user on questions that require identifying the number of designs in a filtered subset of the data or designs that appear in at a particular point in a sequenced set of the data.

Number of Designs: 100									
design_id	cost	reliability	mpg	speed	0% compromise	5% compromise	10% compromise	15% compromise	20% compromise
1	4200	77.1	22.2	89	0	25	50	75	75
2	4050	76.2	20.4	92	0	25	50	75	100
3	4250	79	23.3	88	0	25	50	75	75
4	3500	80	27	81	100	100	100	100	100
5	3550	67.6	17.2	88	50	100	100	100	100
6	3700	76.2	18.2	82	25	50	100	100	100

Figure 5-4: Treatment C – Interactive table

5.3.4 Treatment D: Interactive Table + Visualization

The interface provided to subjects that are assigned into treatment group D combines the bar graph visualization of group B and the interactive features of group C into a single interface. As with group C, participants in this group can input filter expressions into the column header text boxes to update the table. Updates to the table also dynamically update the bar chart to reflect the data remaining within the filters. This application is intended to provide subjects in this treatment group with the combined benefits of both the group B and C applications.

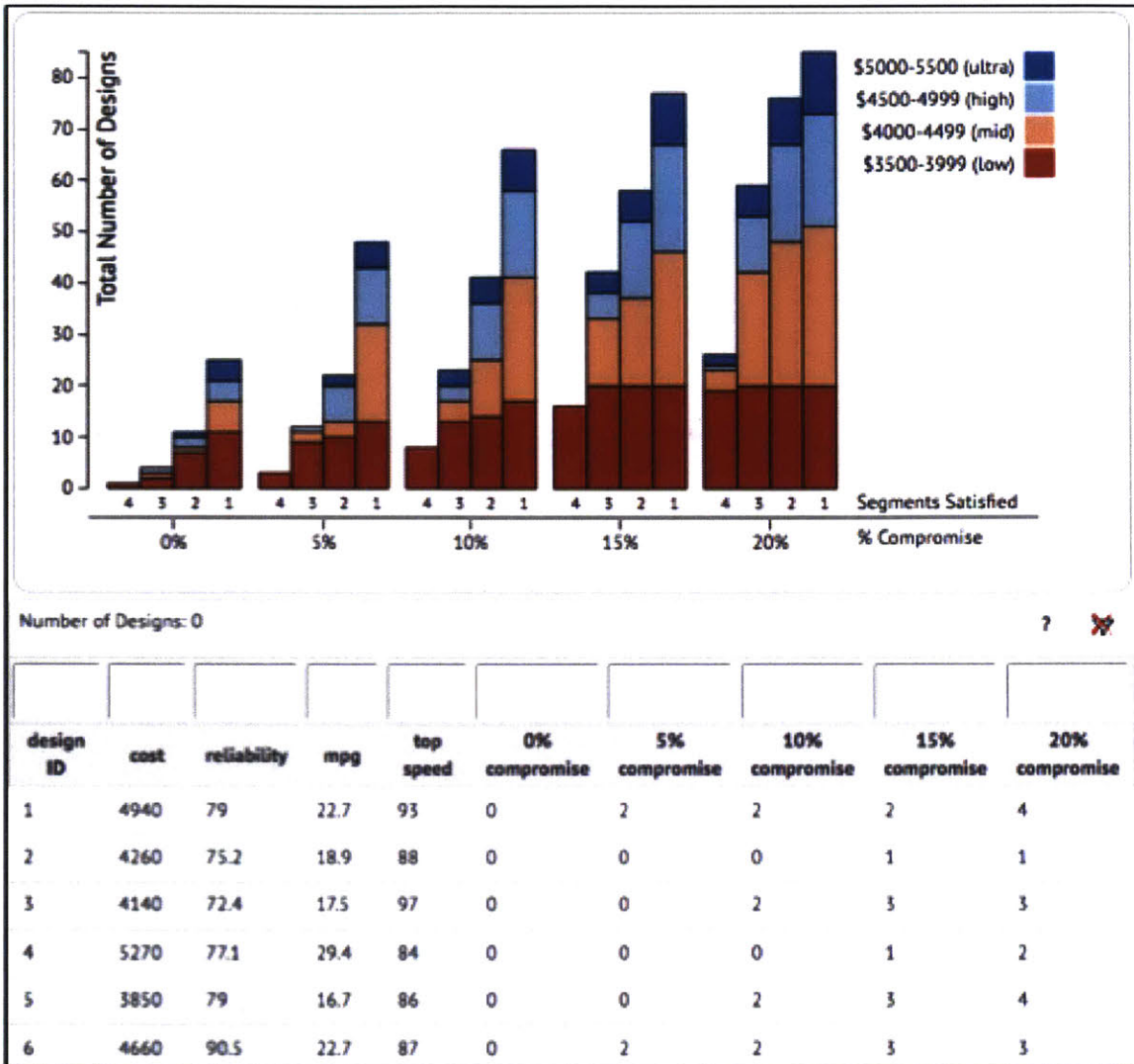


Figure 5-5: Treatment D

5.4 Trial Protocol

Experiment participants, recruited from Amazon's Mechanical Turk (MTurk) online crowdsourcing marketplace, were asked to complete a three part evaluation comprised of:

1. Pre-test questionnaires
2. Experimental design problem
3. Post-test questionnaires

Each experimental session was conducted using a standard procedure sequenced through a script for the Experimentr framework [151]. Subjects' responses to questions and timing data was logged to a database that stored the results as the session progressed.

Participants were allowed to exit the study at any point, and incomplete sessions were not included in the final data analysis. A high-level overview of the test procedure and the data collected at each stage is shown in Figure 5-6.

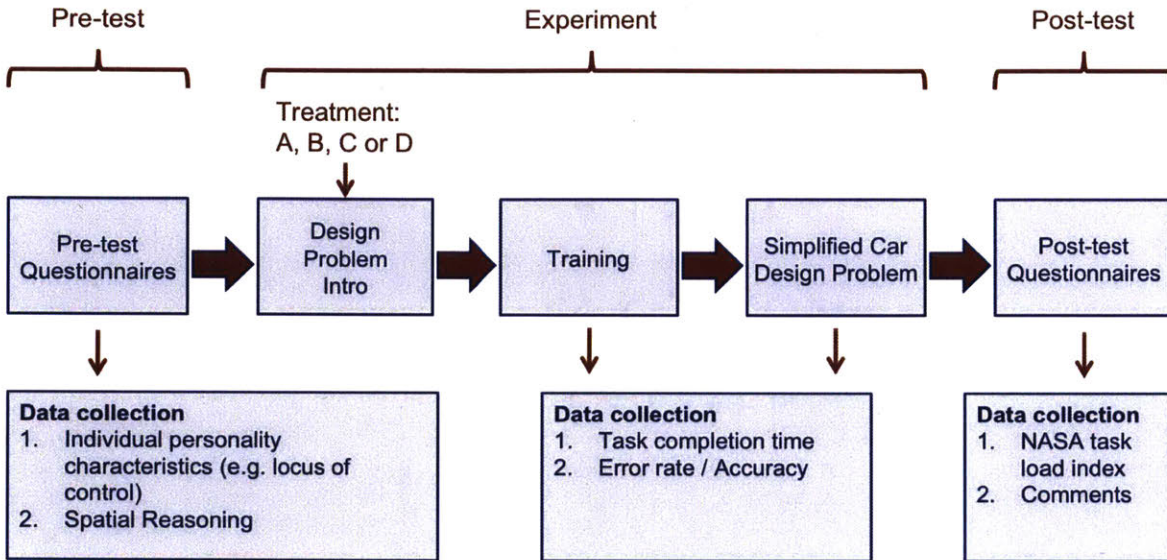


Figure 5-6: Experimental session protocol

The first part of the protocol, the pre-test questionnaires, consists of two separate evaluation tests. The first test evaluates the participant’s spatial reasoning ability. The second test asks participants to complete a survey that evaluates their locus of control and the standard “Big 5” personality traits commonly used in social science research studies. The second part of the protocol, the car design experiment, has three subparts including a problem introduction, training questions with answers, followed by the actual questions about the surrogate engineering design tasks using one of the four previously described web-application interfaces. The interface a subject was given to solve the problem depended on the experimental treatment group to which they had been randomly assigned. After completing the experiment subjects were asked to complete a post-test questionnaire that included an evaluation of their perceived cognitive load and any open-ended comments that they wished to share. Each part of the experimental protocol will be described in detail in the following sections.

5.4.1 Pre-test Questionnaires

Visual analytics research in recent years has generated substantial evidence that individual differences play a role in a user’s ability to effectively use information visualization systems. Spatial reasoning ability is one such factor that has been shown to play a role in human performance when working with such systems [145,152,153]. Another important factor that has received attention is an individual’s locus of control (LOC) [144,154]. A person’s LOC score measures the extent to which they believe

events and their outcomes are within their control versus being driven by outside forces. The two pre-test questionnaires used in this study are intended to evaluate these factors in the experiment participants. This allows any correlations between these factors and test performance to be observed and the impact of treatment group assignment on performance to be decoupled. The pre-test questionnaires used in this study are similar those that have been applied in prior studies that examine the impact of individual differences when performing complex visualization tasks.

5.4.1.1 Pre-test Questionnaire 1: Spatial Reasoning Evaluation

The first pre-test questionnaire is designed to evaluate an individual’s spatial reasoning ability. In general, spatial reason ability refers to the capacity of an individual to form a mental model of a multi-dimensional figure and then mentally manipulate that figure to draw conclusions. For instance, someone with higher spatial ability is likely to be more capable of mentally generating a representation of what an object may look like after it has been rotated and/or translated in space.

To evaluate spatial reasoning ability, several standardized cognitive tests like the VZ-1 (Form Board), VZ-2 (Paper Folding), and VZ-3 (Surface Development) tests from the Kit of Factor-Reference cognitive tests are produced by Educational Testing Service (ETS). Given that this particular study is administered through a web browser the paper-folding test was selected as the most appropriate test. This is also consistent with other studies that have applied the test to measure spatial reasoning ability [145]. The test requires participants to imagine folding a square piece of paper using some sequence of folds, punch a set of holes, and then unfold it. Participants are then asked to identify which pattern of holes would result in the unfolded sheet of paper after the holes have been punched through the arrangement of folds. An example problem given in the instructions for the test is shown in Figure 5-7.

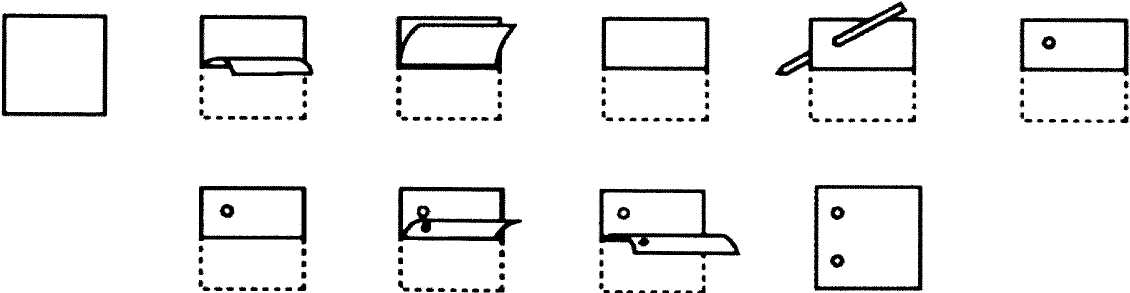


Figure 5-7: Example paper folding question with solution

The test is comprised of 2 groups of 10 questions each were asked for a total of 20 questions overall. Each group of 10 questions had a three-minute time limit. An individual’s spatial reasoning score is based on the number of answers they get correct minus some fraction of the number they get incorrect to discourage guessing. A few

samples of some of the paper-folding questions asked during the survey are shown in Figure 5-8. After completing this test subjects were allowed to take an untimed break if they needed one or they could proceed directly to the next questionnaire.

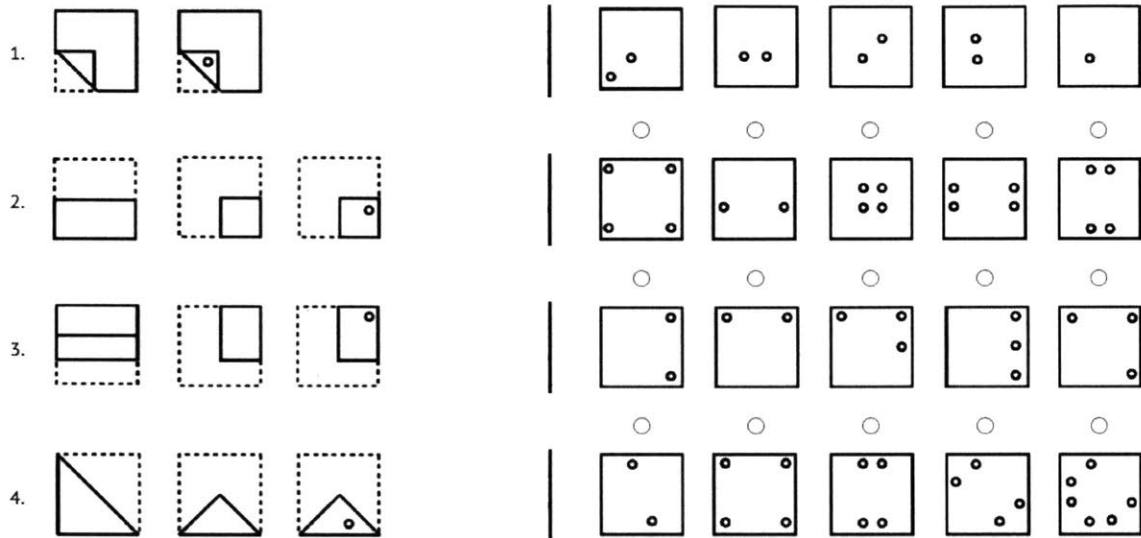


Figure 5-8: Sample of the paper folding questions

5.4.1.2 Pre-test Questionnaire 2: Personality Inventory

Prior research has demonstrated that personality factors, such as locus of control and other cognitive traits, are often correlated with speed and accuracy on visual analytic tasks. To evaluate these personality factors in the participants of this study a second pre-test questionnaire was administered prior to the design experiment part of the protocol. The 27-question personality survey used in this study is the same as the one used in a study by Brown et al. [144]. The survey mixes together questions from a standard Big Five Personality Inventory (20 questions) [155], Locus of Control Inventory (5 questions) [156], and attention checks (2 questions). The questions give the subjects statements that they must then rate on a 5-point scale from inaccurate to accurate as shown in Figure 5-9. The attention checks have a clear and precise answer (e.g. “select option 3”) and can be used to identify survey participants that are just randomly clicking answers. The test provides scores for each participant on scales of extraversion, agreeableness, openness, conscientiousness, neuroticism and locus of control. After completing this questionnaire participants are offered an untimed break before moving on to the surrogate design task part of the protocol.

1. I believe that my success depends on ability rather than luck.	Inaccurate	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Accurate
2. I am the life of the party.	Inaccurate	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Accurate
3. I sympathize with others' feelings.	Inaccurate	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Accurate
4. I get chores done right away.	Inaccurate	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Accurate
5. I have frequent mood swings.	Inaccurate	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Accurate
25. I seldom feel blue.	Inaccurate	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Accurate
26. I do not have a good imagination.	Inaccurate	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Accurate
27. I believe in the power of fate.	Inaccurate	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Accurate

Figure 5-9: Personality factors inventory

5.4.2 Experimental Task

The second part of session, the experimental task, has three subparts: (1) the problem introduction and task overview, (2) training questions, and (3) Nine experimental questions of varying types that must be answered using the interface associated with the subject's randomly assigned treatment group. Subjects' answers to each question are recorded and scored as either correct or incorrect to gauge task accuracy. Timing data is also recorded separately for every part of the experimental task including how long subject spend on the problem introduction, training tasks and each individual question.

5.4.2.1 Problem Introduction and Task Overview

To provide the participants with some context and background for the problem they are first introduced to a design problem for a hypothetical car manufacturing company. The company has multiple designs to choose from and is attempting to sell the car they produce to multiple customer segments. By asking certain customer segments to compromise slightly on what they willing to accept more of the customer segments can be satisfied. This problem is directly analogous to robust design problems of the type that are often encountered in multi-epoch analysis. This strengthens the claim to ecological validity of the experiment because it closely resembles the real-life applications intended for practicing engineers as described in Chapter 4 and demonstrated in the case studies of Chapters 6 and 7 of this thesis.

The problem introduction is identical for all treatment groups, but the instructions on how to use the interface that they have been assigned varies. As an example, the exact text of the introduction and instructions given to subjects in treatment group D is as follows:

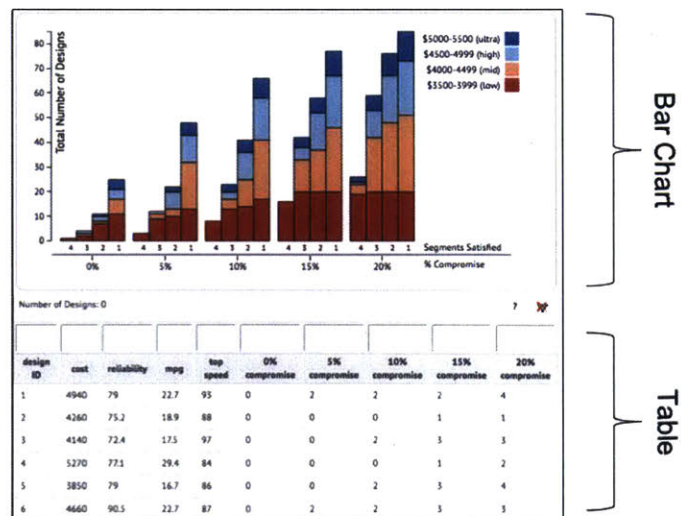
Background

For the following task imagine that we are a car company and our engineering team has been asked to choose the new design that we will produce from a list of 100 options we're currently considering.

We have data on each of these designs for how much they will **cost** and how much performance they deliver in terms of **reliability**, **fuel efficiency** and **top speed**. We would like to sell this car to **4 distinct customer segments** that each have different preferences for cost and performance level of the given metrics. For instance, some customers give more weight to fuel efficiency and others may prefer a car with a high top speed.

For simplicity, assume that we can aggregate all the cost and performance data for each design into a single score called **% compromise**. This score measures the amount a car design deviates from what the customer would consider the best level of performance for its cost. A compromise value of 0% would mean that the design is perfect for that customer. Since each customer segment values something a little different each design can and typically does have 4 different compromise value scores corresponding to the different customer segments. Ideally we would want to find designs that require 0% compromise and satisfy all 4 customer segments at the minimum cost, but this can be challenging.

Our objective for this problem is to examine some data on the 100 car designs we are considering using an interactive web-based analysis tool which is shown in the screenshot to the right. The analysis tool provides 2 main parts: (1) **Interactive Bar Chart** (2) **Interactive Table**

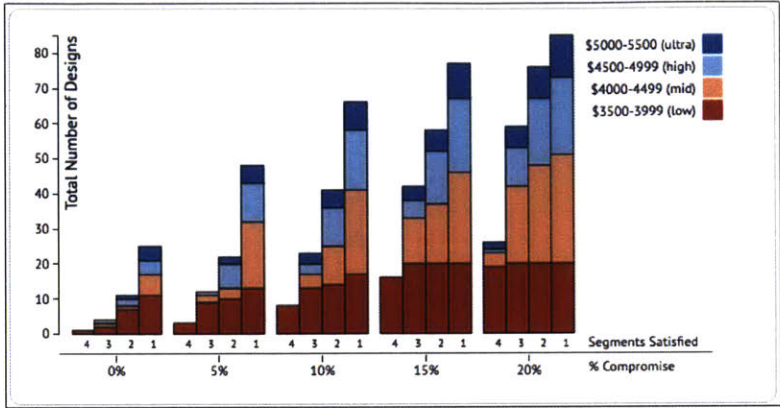


The 2 parts are coordinated which means that when data is filtered out of the table this is reflected in the bar chart as well. A more detailed description of how both the interactive

bar chart and the interactive table work is provided below. Click next at the bottom of the page when you're ready to begin.

Interactive Chart Overview

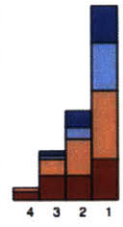
Stacked and Grouped Bar Chart
 The bar chart displays the total number of designs matching the currently applied data filters. There are 5 groups, each containing 4 stacks of up to 4 color coded bars.



(Stacks) Each stack contains up to 4 bars which are color coded according to the legend on the right of the chart. The number 1 immediately below this stack indicates that it represents the number of designs that satisfy at least 1 customer segment.



(Groups) Each group contains 4 stacks. The stack on the left represents the number of designs that satisfy all 4 customer segments. Next, is the stack that represents designs that satisfy at least 3 customer segments, and so on.



(Chart) Reading from left to right the 5 groups correspond to an increasing compromise value from 0% to 20%.

Interactive Table Overview

Data Filters
 Set data filters here by typing an expression into the box above a column and then hit enter. Note in the examples below that the expression should be entered without the quote marks.

Examples:

- ">=75" in the reliability column returns all design with a reliability greater than or equal to 75.
- "<=4500" in the cost column returns all designs with a cost less than or equal to \$4500.
- ">=1" in the 10% compromise column returns all the designs that satisfy at least 1 customer segment at the 10% compromise level.

Count of Satisfactory Designs
 How many designs satisfy the current filters

Clear all filters button
 Click here to clear any previously set filters

Number of Designs: 100

design_id	cost	reliability	mpg	speed	0% compromise	5% compromise	10% compromise	15% compromise	20% compromise
1	4200	77.1	22.2	89	0	25	50	75	75
2	4050	78.2	20.4	92	0	25	50	75	100
3	4250	79	23.3	88	0	25	50	75	75
4	3500	80	27	81	100	100	100	100	100
5	3550	67.6	17.2	88	50	100	100	100	100
6	3700	76.2	18.2	82	25	50	100	100	100

Column Sorting
 Click on any column header to sort the data table by that value

5.4.2.2 Practice Tasks

To allow subjects an opportunity to try out the interface associated with their treatment group before answering the actual experimental tasks they are provided with three training questions. The three training questions correspond to the three task types that make up the experimental tasks. The three training questions with solutions and descriptions of how to use the tool to find that solution are given in a text box above the interface. Subjects can spend as much time as they like to familiarize themselves with the interface.

The training questions provided are identical for each treatment group, but the description of how to solve the problem using the interface varies. As an example, the exact text of the training section given to subjects in treatment group D is as follows:

Here are some quick practice questions before we get started.

Practice question 1: *How many designs have an mpg greater than or equal to 20?*

Solution: *Type “>=20” in the column above “mpg” and hit enter. You should see that there are now 51 designs remaining that match this filter*

Practice question 2: *Of the designs with an mpg greater than or equal to 20, how much does the most expensive one cost?*

Solution: *Without clearing the previous filter, click on the header of the cost column to sort the remaining data by cost. You should see that design 66 is the most expensive at a cost of \$5490.*

Practice question 3: *Of the designs that have an mpg greater than or equal to 20 and satisfy at least 3 customer segments when we allow 15% compromise, which cost category is the smallest?*

Solution: *Without clearing the previous filter, type “>=3” in the column above “15% compromise” and hit enter. You can now look at the stacked bar above the 3 in the 15% group and see that the dark blue block is the smallest. This block corresponds to the “ultra” cost group which is the smallest category. You can also hover the mouse pointer over each block to find out how many designs are in each category.*

5.4.2.3 Experiment Tasks

The main experimental task consisted of nine questions of three different task types. Finding a single taxonomy of task types used for visual analytic applications is challenging. Therefore, the three task types used in this experiment are not intended to be representative of all the possible tasks that a user might engage in when working with all such applications. Rather, the task types chosen for this experiment are intended to best represent some of the most frequently performed tasks in the types of interactive visualizations described in Chapter 4 and demonstrated in Chapters 6 and 7. Again, the

intent here is to strengthen the claim to ecological validity of the experiment by making it closely resemble the intended real-world application to engineering design. The three task types are as follows:

1. **Filtering** – these tasks ask users to identify or count some subset of the data points based on some criteria that apply to one or more data dimensions.
2. **Sorting** – these tasks require data to be ordered numerically or alphabetically to answer the question.
3. **Trend / pattern observation** – these tasks require the identification of a pattern in the data across groups or categories. For instance, determining which group of data points is larger or smaller.

The nine questions of the main experimental task can be divided into three groups. Each of the three groups has one question of each task type. The primary difference between the three groups is the number of data points that must be evaluated in order to answer the given question. The first group of three questions in the experiment only has 7 possible car designs to consider which mean that for the most part they can be easily answered with or without assistance. As the experiment progresses the number of data points that must be considered increases. The second group of questions has 25 candidate car designs and the third group has 100. Varying both task type and the number of data points makes it possible for the experiment to provide better visibility into how factors related to the questions couple with variations in treatment groups to influence human performance. The nine questions are provided in the Appendix in section 9.3.

5.4.3 Post-task

After completion of the nine questions related to the surrogate design task the third and final part of the experiment session ask subjects to provide feedback on their perceived level of effort while completing the tasks with the interface they were assigned. The web interface, as shown in Figure 5-10, allows subjects to provide subjective evaluations of five different factors by moving a slider along a continuous scale. The factors, taken from NASA's Task Load Index (TLX) survey [157], provide a standard means of assessing cognitive load that has been applied in numerous prior research studies [158,159]. This suggests that it can provide a reasonable estimate for this study of the differences in perceived cognitive load between treatment groups. Results of this evaluation are described in the analysis section of this chapter.

How mentally demanding was the task?

Very Low _____ Very High

How hurried or rushed was the pace of the task?

Very Low _____ Very High

How successful were you in accomplishing what you were asked to do?

Perfect _____ Failure

How hard did you have to work to accomplish your level of performance?

Very Low _____ Very High

How insecure, discouraged, irritated, stressed, and annoyed were you?

Very Low _____ Very High

Figure 5-10: Screenshot of Web Interface for NASA Task Load Index Assessment

When the results of the NASA TLX survey are submitted the subject is taken to the last screen of the survey shown in Figure 5-11. This screen allows them to submit any open-ended feedback they have about the test. This is especially useful for subjects that want to provide information that was not directly asked for previously in the test such as possible software bugs or feedback on how the tools could be improved. The final screen also provides them with a randomly generated code that can be linked to their experimental session. This code is then copied and pasted back in to Amazon's Mturk interface so that the subject can receive credit for completing the task and so that their session results can be linked to their unique Amazon worker ID number. This allows an anonymized record to be kept of subjects that have completed the experiment so that they may complete the test only once.

Please copy and paste the following code back on Mechanical Turk before closing this window:

iwz6vm22

Thank you again for your participation. Feel free submit any additional comments below.

Leave feedback here

Submit

Figure 5-11: Screenshot of Feedback Form

5.5 Analysis

This experiment was designed to measure several metrics related to human performance. The three primary responses measured by this experiment were:

1. **Task accuracy**
2. **Task completion time / speed**
3. **Cognitive load**

Prior to conducting the experiment it was hypothesized that the treatment group to which the subject was assigned would influence these responses. As discussed, the treatment group is defined by two primary controlled experimental factors related to the interface subjects were given to answer questions: (1) Presence or absence of a graph, (2) Presence or absence of an interactive capability. Other controlled factors related to the questions asked were also varied to identify how treatment group effects interacted with specific types of questions and the number of data points they required the subject analyze. Beyond these controlled factors there were also variables in this experiment that were believed to potentially impact performance that could not be controlled, namely the individual personality differences of the subjects.

A summary of the overall results of the experiment is shown in Table 5-1. At a high-level it seems clear that treatment group does indeed impact all three primary response variables. Adding either a graph or interaction appears to increase overall accuracy 6-11% and the results are cumulative when both are provided to subjects. Average completion time for the experiment question seems primarily driven by whether an interactive capability was provided. Lastly, cognitive load also appears to be affected by treatment group with each of the experimental treatment groups showing a reduced load relative to the control group. At a high-level it does appear that treatment group

impacts all the response to some degree, but it is not clear if there are other driving factors. To determine how treatment group effects may interact with other variables each of these responses will be analyzed in further detail in the following sections.

Table 5-1: Overall impact of treatment group

Treatment	Graph?	Interactive capability?	Overall Accuracy	Average Completion Time (minutes)	Cognitive Load
A (control)	No	No	73.9%	14.3	0.483
B	Yes	No	85.5%	13.4	0.386
C	No	Yes	80.3%	8.1	0.345
D	Yes	Yes	90.6%	7.7	0.387

5.5.1 Impact on Task Accuracy

The shift in both mean and variance of task accuracy due to treatment group assignment is shown in Figure 5-12. These high-level results suggest that treatment group does have an impact on task accuracy, but a more detailed analysis shows that other factors are important as well. An n-way ANOVA of these shifts in the overall accuracy shows statistically significant main effects due to presence of a graph ($p=0.023$), presence of interaction ($p=0.013$) and spatial reasoning ability ($p=0.015$). This suggests that both the controlled factors of the experiment as well as individual differences play a role in task accuracy. Further segmentation of the data provides some potentially intuitive reasons for this.

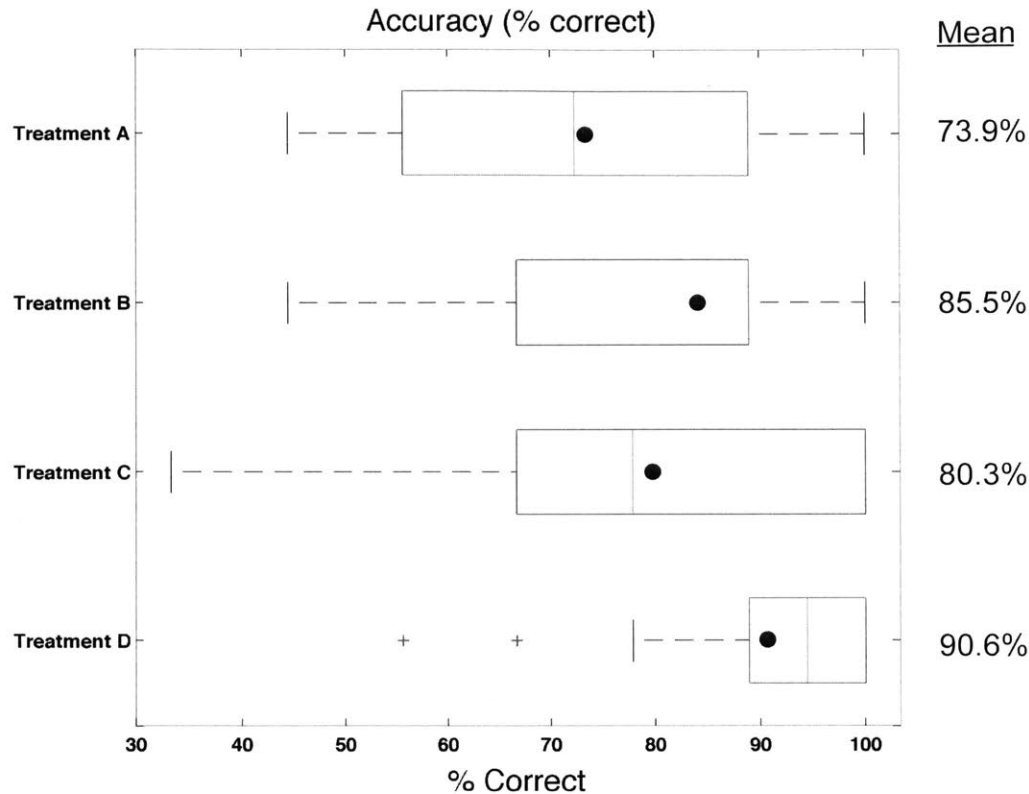


Figure 5-12: Overview of overall task accuracy by treatment group

Examining the difference between treatment groups A and B allows the impacts associated with the addition of a visual representation or graph of the data to be assessed. Table 5-2 shows the average results from the 26 participants in each treatment group. The addition of a graph for participants in treatment group B increased the average number of correct answers by 11% ($p=0.009$). Similar gains can be observed between groups C and D which also differed only in terms of whether participants were provided a graph or not. Participants from group D had a 11% increase in overall accuracy ($p=0.018$) versus group C. Closer inspection of the accuracy results segmented by task type shows benefits of adding a graph were not uniform across all task types. The addition of a graph had no statistically significant impact on filtering and sorting tasks, but increased accuracy on trend observation tasks significantly. Group B had a 34% increase in trend task accuracy over group A ($p<0.001$), and group D had a 35% increase over group C ($p<0.001$). This is perhaps an intuitive result since the intended purpose of using a chart or graph is to identify patterns in data through a visual abstraction.

Table 5-2: Impact of treatment group on task accuracy

Treatment	Graph?	Interactive capability?	Overall Accuracy	Filter tasks	Sort tasks	Trend tasks
A (control)	No	No	74%	90%	74%	58%
B	Yes	No	85%	94%	71%	92%
C	No	Yes	80%	99%	90%	53%
D	Yes	Yes	91%	95%	88%	88%

Examining the difference between treatment groups A and C allows the impacts associated with the addition of an interactive capability to be assessed. Similarly, comparing group B to D is demonstrative because the only difference is whether an interactive capability was provided. Table 5-2 shows that the addition of interaction increased the average number of correct answers by 6% ($p=0.011$) for participants in treatment group C and 11% ($p=0.011$) for participants from group D. Closer inspection of the accuracy results segmented by task type shows those participants that were given an interactive capability primarily benefited on tasks that asked them to filter or sort the test data. Group C participants had a 9% increase in accuracy ($p=0.048$) on filtering tasks and a 16% increase in accuracy ($p=0.022$) on sorting tasks relative to the control group. Group D participants had similarly high scores on filtering tasks, but had a 17% increase in accuracy ($p=0.018$) on sorting tasks when compared to group B. This effect is more pronounced as the number of data points increases. Since the intended purpose of the interactive capability in the interfaces developed for this study are to assist in sorting and filter this is again a somewhat intuitive result.

Effects related to treatment group are not the only factor driving overall task accuracy. Individual differences in the subjects appeared to have an impact. Of the six measured personality characteristics only spatial reasoning ability had a statistically significant impact. Interestingly, spatial reasoning ability does not impact all treatment groups in the same way. As shown in Table 5-3 there is very little correlation between spatial reasoning ability and accuracy in the control group. However, the correlation is much higher if we add either interaction or a graph. When we add both a graph and interaction the effects are not quite cumulative, but definitely higher than the individual effects. Participants in group D that had both saw a 2% increase in accuracy on average for every 1-point higher they scored on the spatial reasoning survey.

Table 5-3: Correlation between overall accuracy and spatial reasoning ability

Treatment	Graph?	Interactive capability?	Correlation between spatial reasoning and overall accuracy
A (control)	No	No	0.16
B	Yes	No	0.43
C	No	Yes	0.53
D	Yes	Yes	0.62

5.5.2 Impact on Task Completion Time

The shift in both mean and variance of task completion time based on treatment group assignment is shown in Figure 5-13. These high-level results suggest that treatment group does have an impact on task completion time, but a more detailed analysis shows how the factors that influence completion time differ from those that impact task accuracy. An n-way ANOVA of these shifts in the overall task completion time shows statistically significant main effects due to presence or absence of interaction ($p < 0.001$), but other factors do not appear to be statistically significant at this level of analysis. Further segmentation of the data provides some additional insights into how task completion time is impacted.

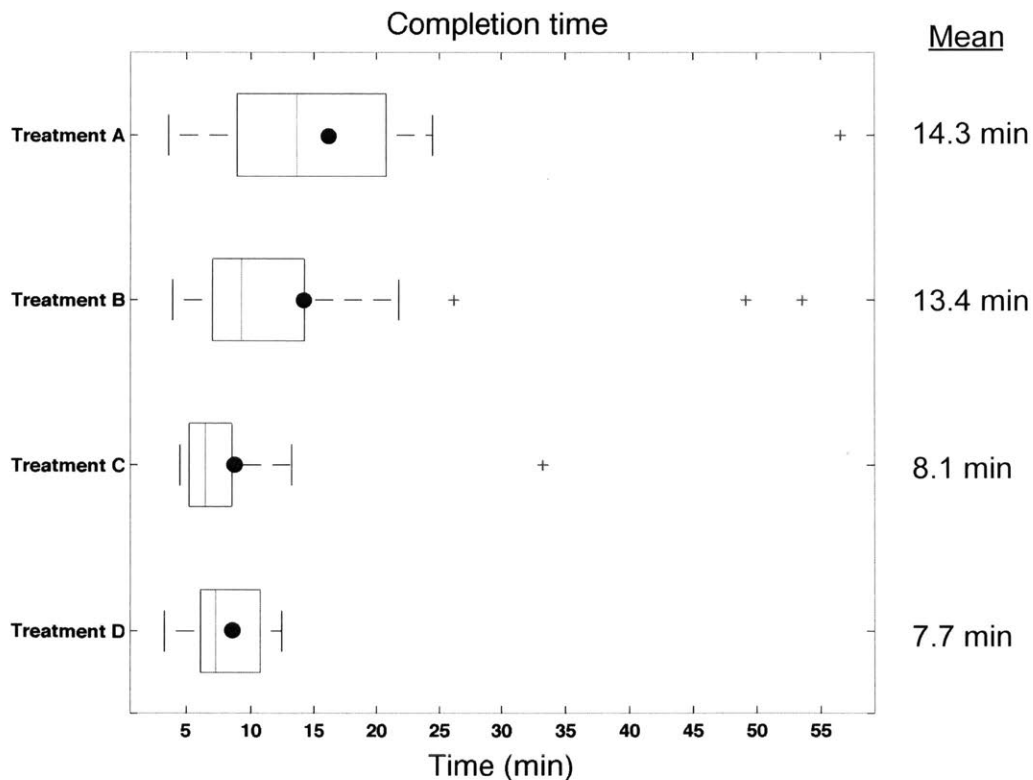


Figure 5-13: Overview of experiment completion time by treatment group

To observe any effects due to the addition of a graph groups A and B can be compared, or similarly groups C and D that only differ in whether the interface offers a graph or not. As the results of the ANOVA demonstrate, there is no statistically significant difference in overall task completion time between either of treatments within each of the pairs. However, if the data is segmented by task type a small, but statistically significant, decrease in task completion time can be observed on trend observation task for group B and D participants. As shown in Table 5-4 completion time on trend observation tasks are cut nearly in half going from group A to B ($p=0.004$). Going from group C to D reduces the completion time for trend observation tasks from an average of 1.53 to 0.93 minutes ($p=0.050$). The difference in task completion time for trend observation tasks grows wider as the number of data points that must be examined in the question increases. This suggests that a visual representation does have an impact on completion time for trend observation tasks and the benefits become even more important with increasing data volume. Interestingly, while the addition of a graph appears to benefit trend observation tasks it seems to result in a slight increase in completion times on filtering and sorting tasks where the graph is not needed to solve the problem. This may be driven by the fact that the user has to spend a few seconds scrolling by the graph or they may be spending some time determining whether they need the graph to solve the problem before moving on to the table.

Table 5-4: Impact of treatment group on task completion time (minutes)

Treatment	Graph?	Interactive capability?	Overall Completion Time	Filter tasks	Sort tasks	Trend tasks
A (control)	No	No	14.2	0.85	1.73	2.16
B	Yes	No	13.4	1.23	2.05	1.18
C	No	Yes	8.1	0.46	0.72	1.53
D	Yes	Yes	7.8	0.65	1.02	0.93

From Figure 5-13 it is clear that participants in groups C and D, which had an interactive capability, could complete the task questions significantly faster. The results of the ANOVA also confirm that overall task completion time is effected by interaction and the results are statistically significant. As shown in Figure 5-14 to Figure 5-16, if the data is again segmented by task type even more insights can be derived about the nature of this effect.

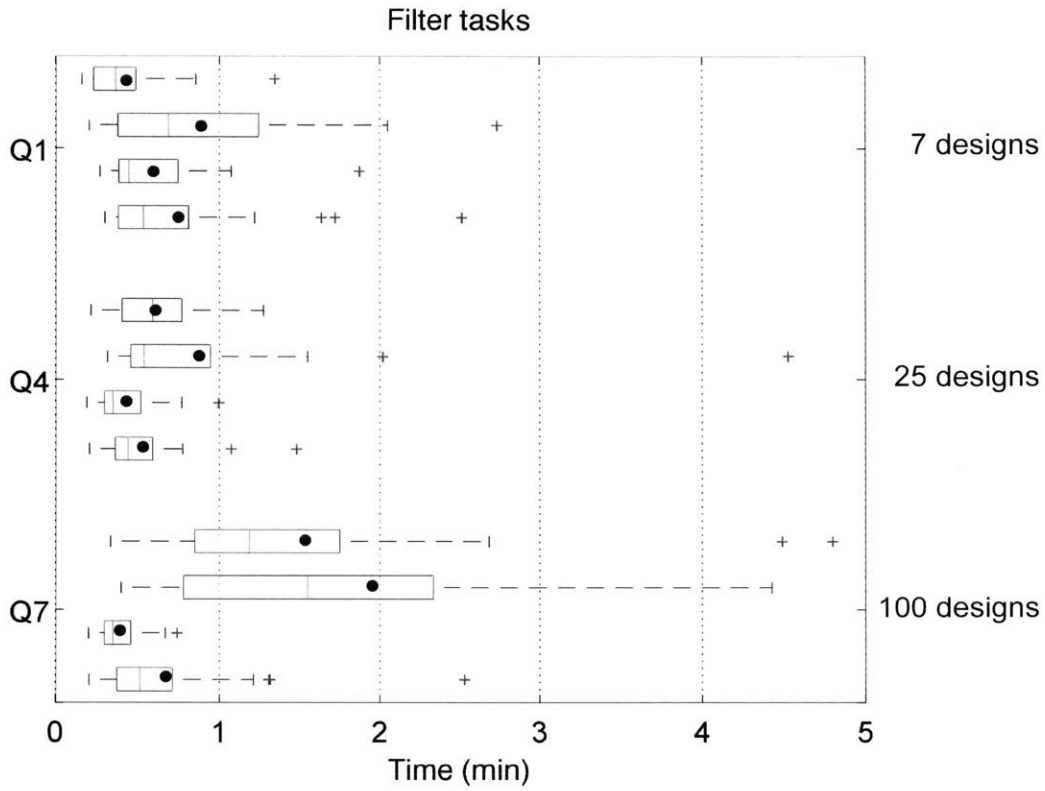


Figure 5-14: Completion time for filter tasks

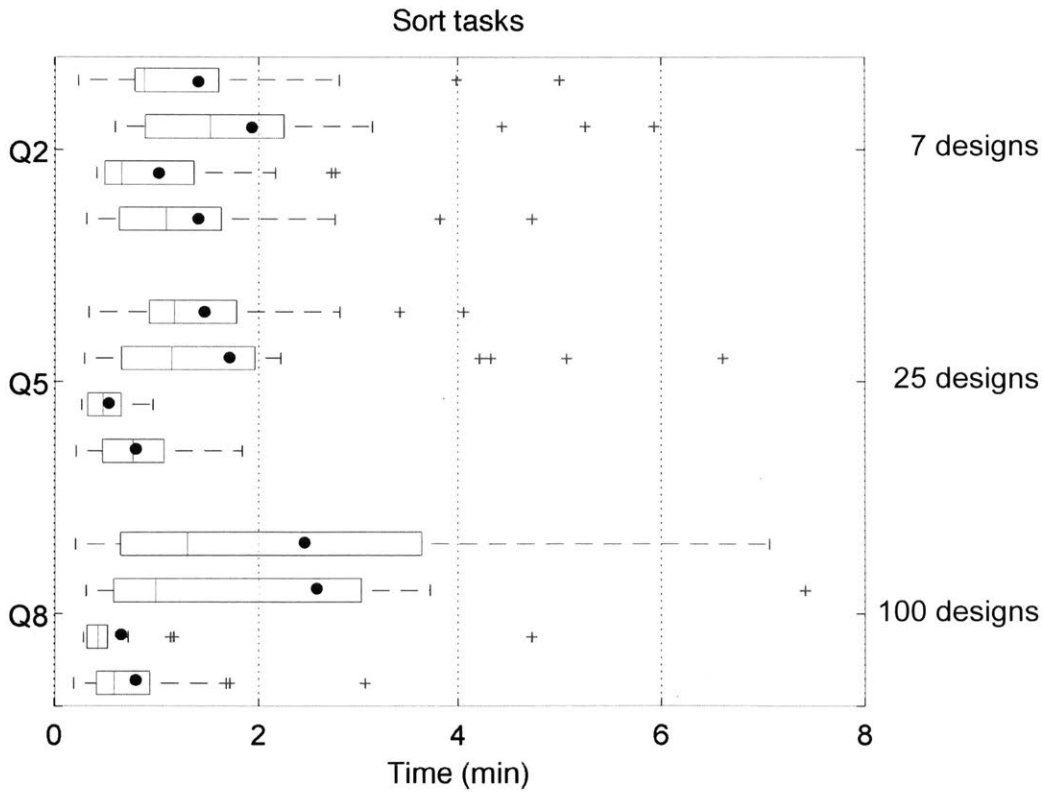


Figure 5-15: Completion time for sorting tasks

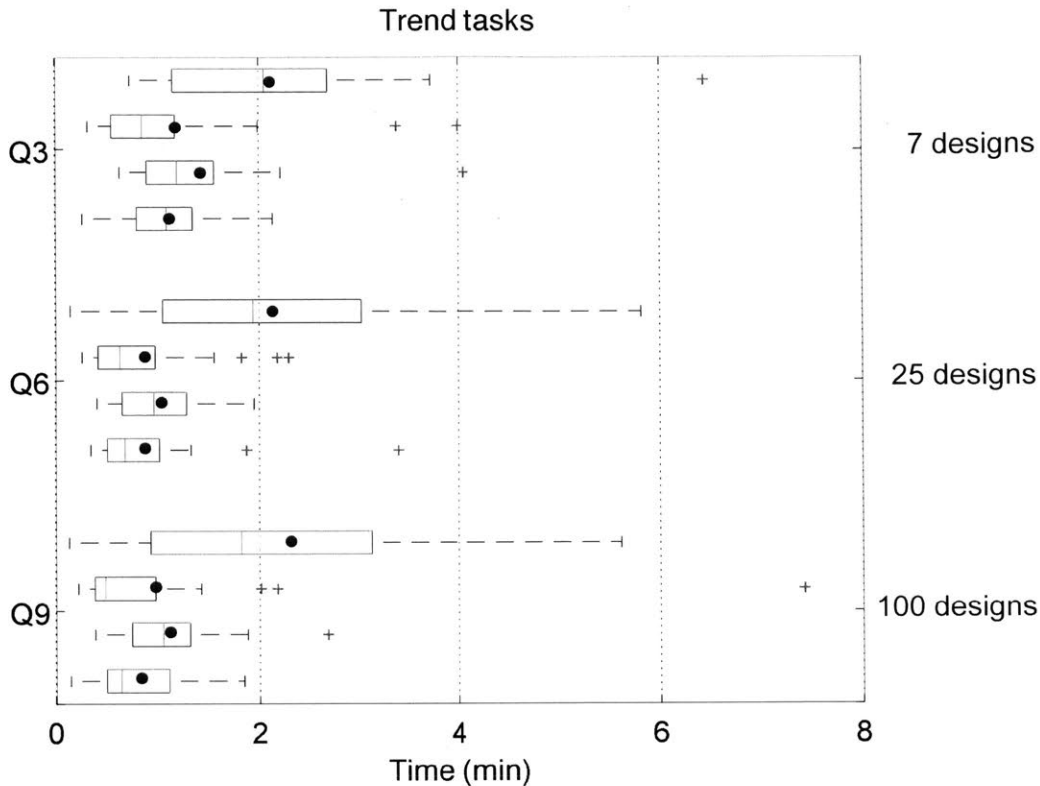


Figure 5-16: Completion time for trend observation tasks

First, examining the difference between group A and C, neither of which had a graph, shows that the addition of interaction reduced overall task completion time from 14.2 to 8.1 minutes ($p < 0.001$). This difference is almost entirely driven by reductions in task completion time for tasks that required the analysis of 25 or more data points. This seemed to be the case regardless of task type. Comparing groups B and D, which both had graphs, tells a story that is similar, but subtly different. The addition of interaction in this case reduced overall task completion time from 13.4 to 7.8 minutes ($p = 0.012$). As with previous pair, the benefits in this case are almost entirely observed on task that required the analysis of 25 or more data points, but for this pair it was only on filtering and sorting tasks. This suggests the addition of interaction provides no further benefits when answering trend observation question if a subject has already been given a graph. However, if they have not been given an appropriate graph to answer the question they can use the interactive capability to compensate on trend observation questions. The other main take-away from this analysis is that whether an interactive capability is available or not becomes more important with increasing data volume.

As the results of the ANOVA suggest, none of the individual personality characteristics measured by this experiment appear to have significant correlations with task completion time. As shown in Table 5-5 spatial reasoning ability that appeared to have an impact overall task accuracy does not show any strong correlations with task completion time. Segmenting the results further by task type and number of data points required also shows no statistically significant effects.

Table 5-5: Task completion time and individual differences

Treatment	Graph?	Interactive capability?	Correlation between spatial reasoning and task completion time
A (control)	No	No	0.36
B	Yes	No	-0.32
C	No	Yes	0.11
D	Yes	Yes	0.25

5.5.3 Impact on Cognitive Load

After completion of the surrogate design task subjects were asked to rate their perceived workload while performing the tasks using a standard NASA TLX survey. The survey captured five different cognitive factors as well as a composite score for overall cognitive load. An n-way ANOVA of the composite cognitive load score shows statistically significant main effects due to subjects' spatial reasoning ability ($p=0.038$), but other factors do not appear to be statistically significant at this level of analysis. It should be noted that while the ANOVA does not show an effect due to presence of a graph or presence of an interactive capability it does show statistical significance with treatment group overall ($p=0.008$). From Figure 5-17 it can be observed that the assigned treatment group does indeed seem to have an impact on the subjects' mean composite cognitive load. These results are also summarized in Table 5-6. Specifically, it appears that all experimental groups have similar reductions in cognitive load relative to the control group, but more detailed analysis is needed to understand the effect.

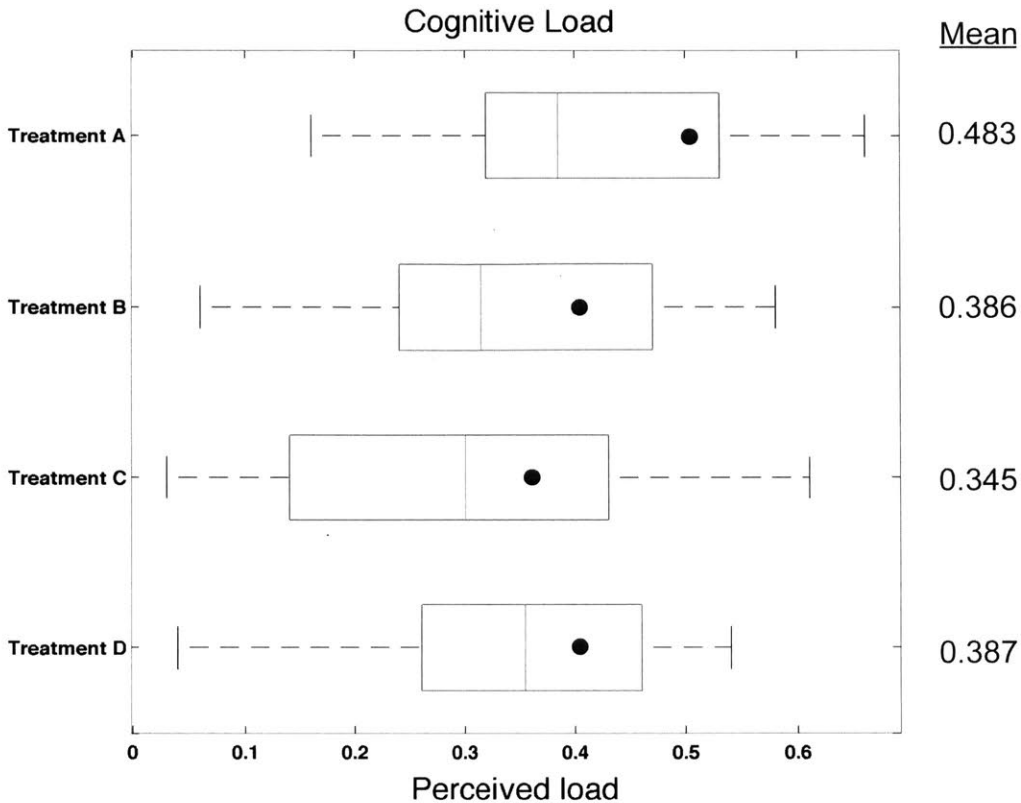


Figure 5-17: Composite Cognitive Load by Treatment Group

Table 5-6: Impact of treatment group on composite cognitive load

Treatment	Graph?	Interactive capability?	Composite Score	% Decrease vs. Control
A	No	No	0.483	
B	Yes	No	0.386	20.1%
C	No	Yes	0.345	28.6%
D	Yes	Yes	0.387	20.0%

Comparing the effects associated with adding a graph an average decrease in cognitive load of 20.1% ($p=0.037$) can be observed between groups A and B. Similarly, when interaction is added, we see a decrease of 28.6% ($p=0.010$) between groups A and C. Combining both visualization and interaction we see a decrease of 20.0% ($p=0.036$) between groups A and D. Shown in Table 5-7, the primary sub-components of cognitive load driving the overall difference between each group are lower levels of mental demand, temporal demand and frustration reported by the subjects. It should also be noted that sub-component of cognitive load that evaluates the level of confidence subjects have in their answers to questions does not show a statistically significant variation between treatment groups. This result is somewhat unexpected given that treatment

groups have indeed been shown in this experiment to have a statistically significant impact on overall task accuracy.

Table 5-7: Sub-components of cognitive load

Treatment	Composite Score	Mental	Temporal	Performance	Effort	Frustration
A (control)	0.483	0.692	0.244	0.379	0.699	0.402
B	0.387	0.621	0.155	0.258	0.654	0.245
C	0.345	0.487	0.164	0.302	0.529	0.245
D	0.387	0.569	0.188	0.284	0.623	0.268

As the results of the ANOVA suggest, spatial reasoning ability is the only individual personality characteristics measured by this experiment that appears to have a significant impact composite cognitive load score. As show in Figure 5-18 spatial reasoning score has a relatively high correlation ($R=0.417$) with composite cognitive load. If we only consider treatment groups that have an interactive capability (groups C and D) the correlation is even stronger ($R=0.556$) as shown in Figure 5-19. These results are interesting because they suggest that individuals may see slightly greater decreases in composite cognitive load for every additional point increase in spatial reasoning score when provided with an interactive capability.

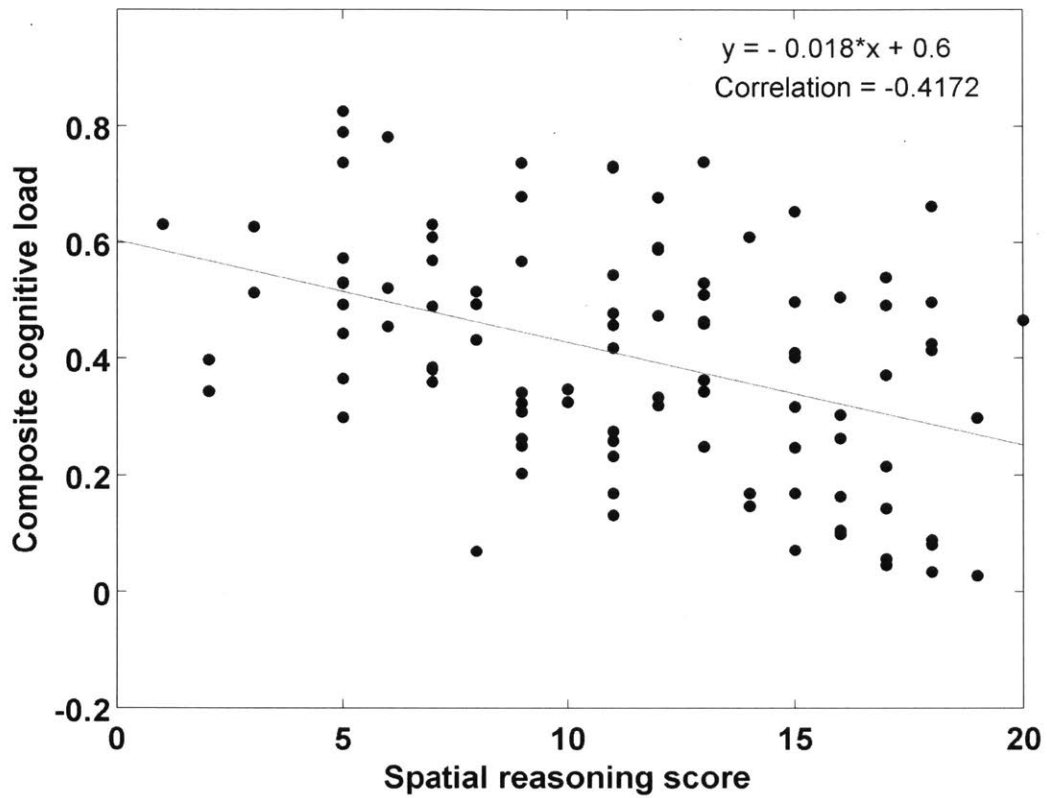


Figure 5-18: Spatial reasoning score versus cognitive load

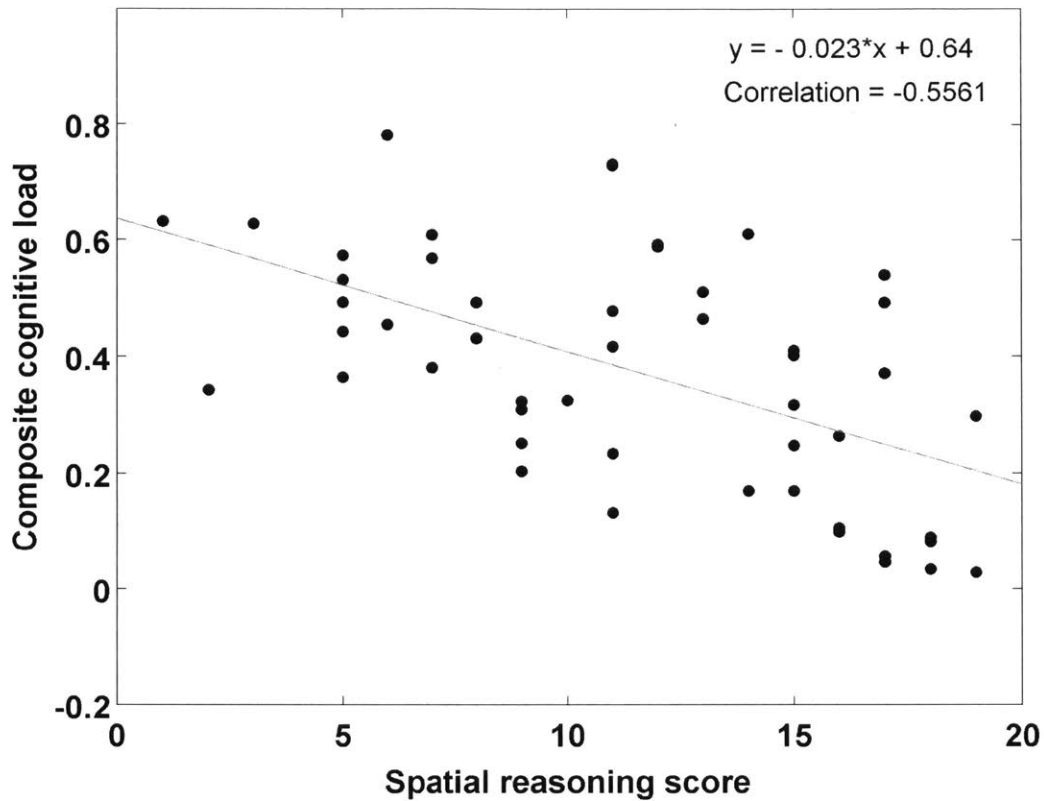


Figure 5-19: Spatial reasoning score versus cognitive load for treatment groups with interaction

5.6 Discussion

This experiment was conducted to better understand if interactive visualization improves decision-making for design problems like those that are the focus of this thesis. To that end, this experiment collected data from human subjects working with various web-based design tools to perform a surrogate design tasks for a simplified car design. By controlling variables associated with the type of interface provided the experiment allows the impacts of visualization and interaction on human performance to be decoupled and evaluated. Additional detail about how individual differences, such as subjects' personality and spatial reasoning ability, influence results can also be evaluated using data collected from pre-test questionnaires. Several conclusions can be drawn from the experimental results about the impact on task accuracy, completion time and cognitive load. The key take-aways from this experiment include:

- **Task Accuracy**
 - The type of interface used to answer design task questions influence task accuracy. Specifically, adding a graph improves accuracy on trend observation tasks and adding an interactive capability improves accuracy on sorting tasks.
 - Presence of a graph or interactive capability becomes more important as the number of data points associated with the task increases.
 - Accuracy is strongly correlated to an individual's spatial reasoning ability when either a graph or interactive capability is present.

- **Completion time**
 - The effects of adding a graph are small, but adding an interactive capability significantly reduces the time required to solve design task problems. This effect is most prominent on tasks that have 25 or more data points associated with them.
 - There is no clear correlation between task completion time and individual personality characteristics.

- **Cognitive Load**
 - Adding a graph or interactive capability reduces cognitive load, but adding both does not further reduce the perceived load.
 - Reported drops in mental and temporal demand as well as lower levels of frustration are the primary drivers of reduced cognitive load.
 - Cognitive load has a strong negative correlation with spatial reasoning ability. As spatial reasoning ability increases cognitive load decreases significantly. This correlation is even stronger when an interactive capability is available.

The contributions of this experiment to this research are significant. This experiment demonstrates the relative contributions of the two primary components of visual analytic systems (representation and interaction) and how they are impacted by factors such as task type, data volume and individual personality differences. Because the surrogate design problem used in the experiment closely mirrors the challenges of an actual multi-epoch design problem the results can offer guidance on how the interactive applications for IEEA should be constructed. These experimental results may also improve future interactive applications intended for engineering system designers.

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6.0 Case Study 1 – Space Tug

To demonstrate the detailed application of the IEEA framework, a case study aimed at designing a multi-mission orbital transfer vehicle, or space tug, was selected. A space tug may be used for a variety of missions including observing, servicing or retrieving an on-orbit spacecraft. The original case study described by McManus et. al [25] is, at first glance, a seemingly simple trade study, but despite the simplicity of the system model the analysis is actually nontrivial. Fitzgerald [30] expanded upon this case as a demonstration of his valuation approach for strategic changeability (VASC). The case study demonstrated here (in 10 processes) replicates the one by Fitzgerald [30] in terms of problem description, but provides for an interesting comparison since the application of IEEA leads to different insights that impact previous conclusions.

6.1 Elicitation

The following subsections describe the processes of the elicitation module of IEEA.

6.1.1 Process 1: Value-Driving Context Definition

The first process defines the stakeholders, problem statement, exogenous uncertainties and the basic value proposition for the system. For this case study the problem statement, as described by Fitzgerald [30], is that the project sponsor would like to develop a space tug that can provide services to customers that collectively have eight different missions they need to perform. The space tug delivers value by meeting the demands of as many of those customers as possible for as long as possible. The ability to do so is driven not just by the nature of a given design alternative, but also by external factors like technology level that directly impact the performance attributes of the system.

6.1.2 Process 2: Value-Driven Design Formulation

The second process begins by defining the needs statements for all stakeholders, from which the attributes of system performance are derived, along with utility functions describing each stakeholder's preference for each attribute. As shown in Table 6-1, for this case study 8 different missions are defined, each with a different weighted preference for three system performance attributes: **payload**, **response time** and ΔV . Payload refers to the total mass the spacecrafts grappling system can handle, response time is modeled only a binary slow or fast, and ΔV measures the total change in velocity the propulsion system can impart on the vehicle to change orbit or perform station-keeping operations. Resource statements that dictate the expense attributes of the system can also be identified. As a simplifying assumption, the only expense attribute for the space tug is the system acquisition cost. Expenses associated with the execution of change options will be discussed separately in the multi-epoch analysis section of this case study.

Table 6-1: Summary of preference weightings for each mission

	Payload	Response Time	ΔV
(1) Baseline Mission	0.3	0.1	0.6
(2) Technology Demonstration	0.7	0.1	0.2
(3) GEO satellite rescue	0.2	0.2	0.6
(4) Satellite Deployment Assistance	0.6	0.3	0.1
(5) In-orbit refueling and maintenance	0.75	0.05	0.2
(6) Debris Collection	0.2	0.05	0.75
(7) All-purpose Military Mission	0.4	0.2	0.4
(8) Satellite Saboteur	0.2	0.2	0.6

The value delivered by a given design alternative is different in each mission because they have different requirements (needs), operationalized as different multi-attribute utility functions to calculate a measure of value based on the performance attributes of the design. For example, in the debris collection mission the single attribute weighting on response time is lower than in the rescue mission because that attribute is less important for that mission. The multi-attribute utility (MAU) function for each mission is developed from the weighted sum of the individual single attribute utilities (SAU). As shown in Figure 6-1, each performance attribute for each mission has a different mapping to a SAU value. For this case study, each is a piecewise linear function, but SAU curves can take on more complex non-linear shapes depending on the needs of a particular stakeholder. Zero is defined as minimally acceptable, with one defined as maximally satisfied. Attributes beyond SAU one is assigned a score of one, while attributes worse than SAU zero is deemed infeasible (unacceptable performance). For each design alternative, after computing the SAUs corresponding to the performance attributes, the MAU value can be computed as a weighted sum of the SAUs for each mission.

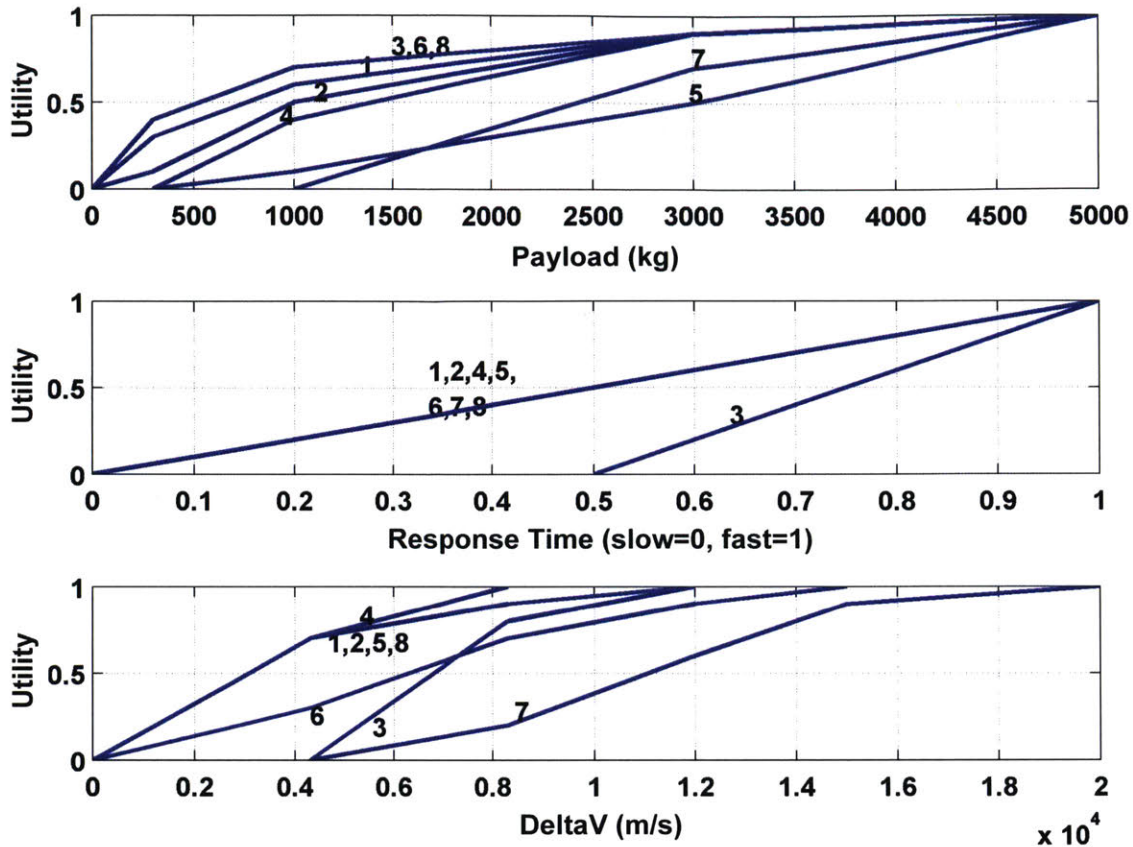


Figure 6-1: Single attribute utility (SAU) curves for the 8 different missions

Ricci, et al. [160] previously discussed a simplified version of the space tug case study as an example of how these SAU functions could be developed, evolved, and weighted using an interactive application. An expanded version of the application described by Ricci was developed for demonstration purposes. As shown in Figure 6-2, an analyst can interact with the SAU function by dragging the points on the right-hand chart to a new position or changing the weighting values. In the example shown here is the values for the ΔV SAU function are updated and the weighting values are changed to show the difference between epoch 1 and epoch 7.

For the case study described in this chapter the SAU functions and weightings are identical to those described by Fitzgerald, but in some cases an analyst may want to explore how different weightings and SAU function shapes impact the tradespace as a whole. A stakeholder may benefit from this type of interaction and real-time feedback if the qualities of the system they believe to be valuable are not well articulated. This type of application is an example of how interactivity can often be a useful or necessary component of this process when eliciting stakeholder value statements.

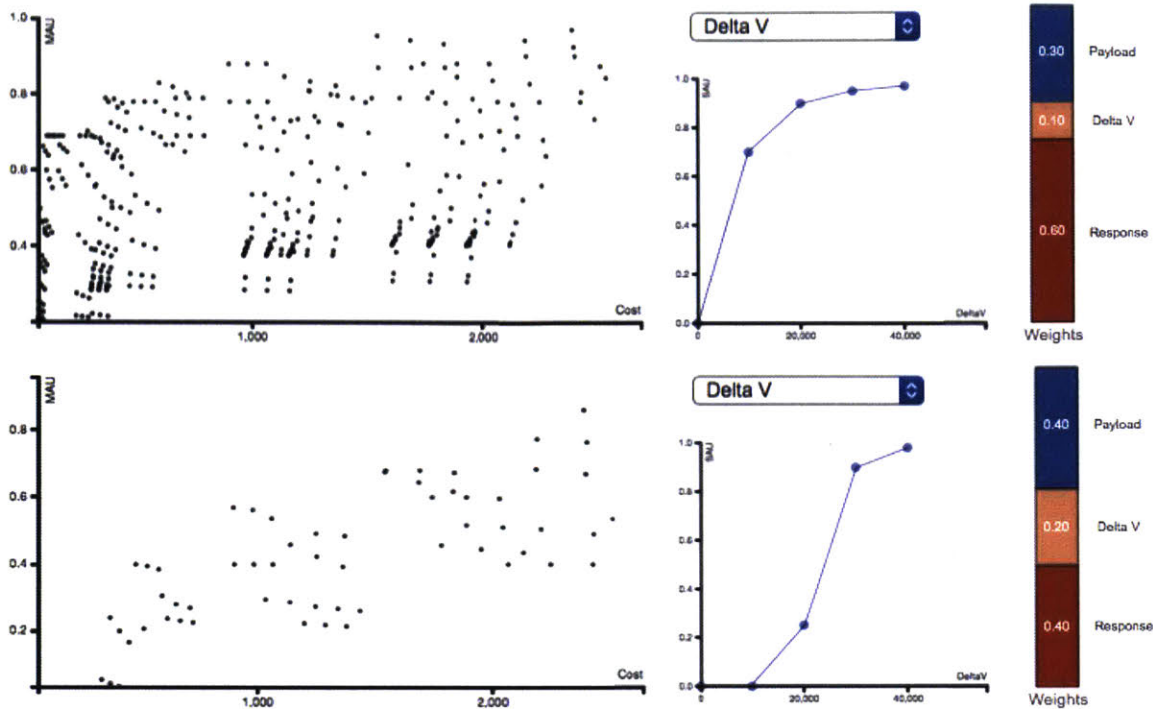


Figure 6-2: Interactive Visualization of SAU function and weightings showing (top) Initial tradespace and preferences over performance attributes corresponding to Epoch 1; (bottom) Modified SAU function and weightings corresponding to Epoch 7

6.2 Generation / Sampling

The following subsections describe the processes of the generation and sampling modules of IEEA.

6.2.1 Process 3: Epoch Characterization

In process 3 the key contextual uncertainties are identified so that epoch variables can be characterized. In addition to different preference sets that have already been described, value delivery for design alternatives in this case study is also affected by a single context variable, technology level, which has two levels: present or future. Technology level can directly impact the system performance attributes through fuel efficiencies and vehicle mass fraction. It can also impact some transition costs when executing change options. A full-factorial design of all combinations of the 8 preference sets and 2 contexts results in 16 epochs as summarized in Table 6-2.

Table 6-2: Summary of Epoch Variables

Epoch Variable	Levels
Mission	1 through 8
Technology Level	Present or Future

6.2.2 Process 4: Era Construction

This process constructs era timelines composed of multiple sequences of epochs each with a set duration to create long-run descriptions of possible future scenarios a system may encounter. Simulating lifecycle performance in this way allows an analyst to evaluate path-dependent effects that may only arise when uncertainty is time-ordered. The activities in this process are in many ways analogous to those used in narrative or computational scenario planning [124]. The future timelines can be constructed manually with the aid of expert opinion (narrative) or by implementing probabilistic models (computational), such as Monte Carlo simulation or Markov chain models, that define epoch transitions.

For this case study eras were constructed according to the rules previously described by Fitzgerald [30]. Each era was created with total length of 10 years and comprised of epochs uniformly distributed in duration between 1 to 12 months. The epochs were assigned one of the 8 mission types corresponding to different users at random. The context variable corresponding to technology level was initially set to a value of “present” and at a randomly drawn point after 5 years it transitions to the “future” state.

6.3 Evaluation

The following subsections describe the processes of the evaluation module of IEEA.

6.3.1 Process 5: Design-Epoch-Era Evaluation

The first four processes defined the relevant elements of the models that will be evaluated in the fifth process. Figure 6-3 shows how the previously defined models are integrated to map design and epoch variables into stakeholder value (MAU) and expense (MAE). Enumerating the levels of the design variable using an experimental design (frequently a factorial design) generates design vectors (**D**) which can be evaluated using the system performance model to output the system cost and a vector of the performance attributes (**A**). Change options (**Δ**) can also be added to the design at an additional cost, but may only provide additional value at some point in the future. The performance attributes serve as inputs to the value model which outputs a value (**U**) for the system. The operating context (**C**) can impact the system performance and the stakeholder needs

(N) can impact the value model. Epoch variables describe the context and needs and are enumerated in a fashion similar to the design variables. When change options are considered, a change strategy must also be assumed. In the event of a perturbation to system value the change strategy will dictate whether a particular change option is executed if available. This may come at an additional cost to exercise the option and likely a change in system value.

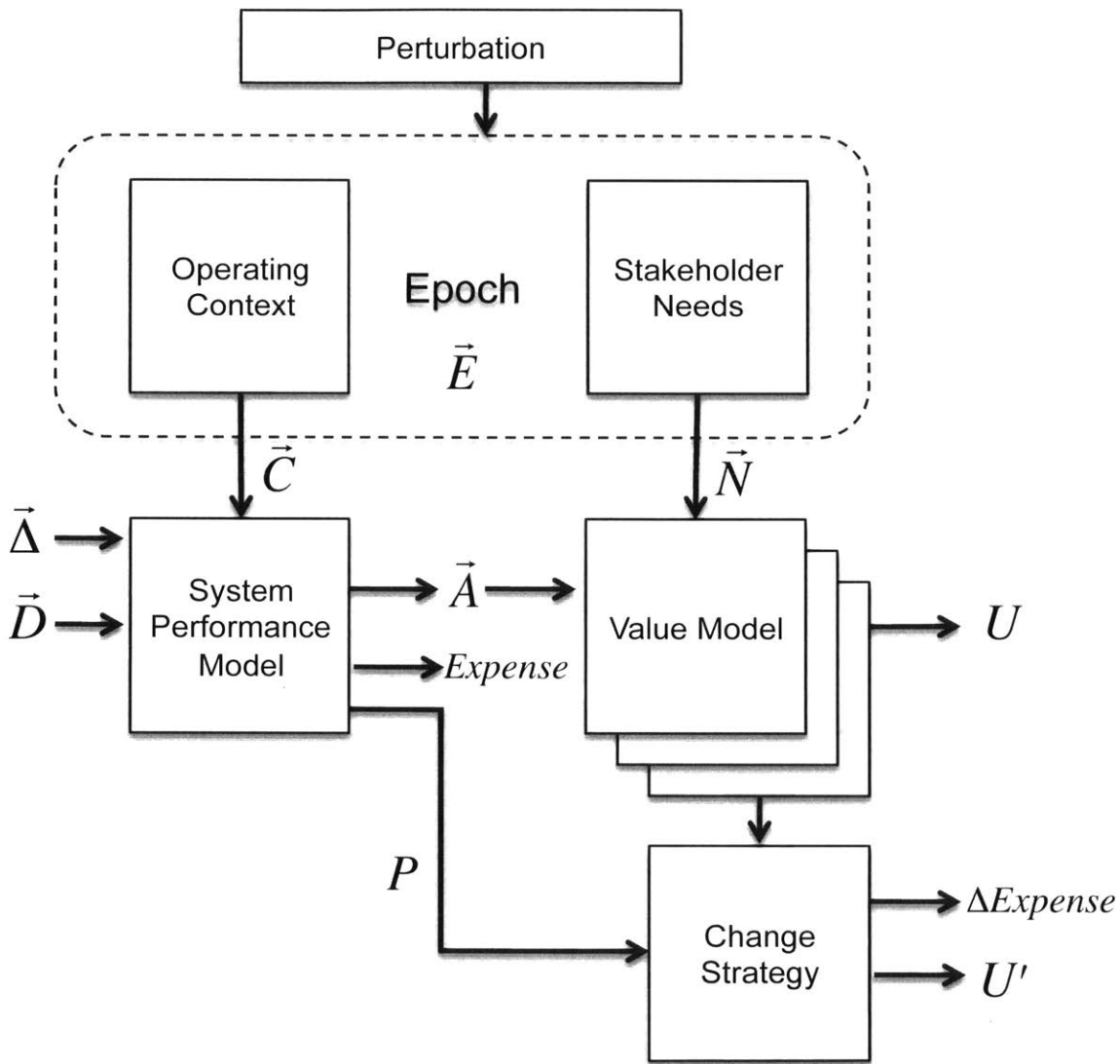


Figure 6-3: Combinations of Design-Epoch-Era evaluated through performance, value, context and strategy models

Fitzgerald [30] chose design variable levels as shown in Table 6-3 below. These are similar to the levels chosen by McManus et al. [25] except that a fourth design variable, design for changeability (DFC) level, is added. Both authors chose to use full-factorial experimental designs to enumerate the space of system design variables. This approach has been repeated here and the range of the evaluated performance attributes is

shown in Table 6-4. A full-factorial enumeration of this space results in 432 designs, but not all designs are feasible. Due to compatibility constraints between propulsion type and fuel mass there are only 384 feasible designs.

Table 6-3: Design variable levels

Design Variable	Levels
Capability	Low, Med, High, Extreme
Propulsion Type	BiProp, Cryo, Electric, Nuclear
Fuel Mass (kg)	30, 100, 300, 600, 1200, 3000, 10000, 30000, 50000
DFC Level	0, 1, 2

Table 6-4: Performance attribute levels across all evaluated designs

Performance Attributes	Range
Cost	[96.9, 3952.8]
Payload	[300, 5000]
Response Time	[slow, fast]
Delta V	[24.4, 41604.0]

Since the space tug system performance model is relatively simple the computational time required to evaluate all design-context pairs is small. For more complex system models, fewer design levels or more sophisticated enumerating via experimental designs, such as central composite or latin hypercube designs, may be required to lower the computational burden. Selecting the best way to enumerate the input space is another potential opportunity for improvement in this process through HIL interactivity, but this has not yet been explored. After evaluating the performance space of available alternatives, the value models developed in process 2 can now be applied to map the performance of each design-context pair into the value delivered in each of the 8 missions. This results in 6,144 design-epoch pairs (384 designs * 2 context * 8 preference sets) to consider. The following sections will discuss how these design-epoch pairs can be better understood through interactive visualization and analysis as demonstrated through various prototype applications.

6.4 Analysis

The following subsections describe the processes of the analysis module of IEEA.

6.4.1 Process 6: Single Epoch Analyses

Single epoch analysis is comparable to what is traditionally thought of in practice as tradespace exploration. Within a given epoch, a scatter plot of cost (MAE) versus

optimal) it can be observed that 16 designs are in the Pareto set. Further restricting this space to the target price range leaves only 2 designs (95 and 96) that are considered acceptable. If an analyst would prefer to broaden the list of acceptable designs they can then play “what-ifs” like relaxing the constraint on the brush filter on the FPN dimension. By relaxing this constraint to 1% it can be shown that 71 designs are within this near-optimal range of the Pareto front and 5 of them (95, 96, 224, 319, 352) are in the acceptable price range as shown in Figure 6-5.

Certain patterns become clearly visible as the space is filtered and explored. For instance, by examining the parallel coordinates and interactively assigning radius and color to various dimensions it can be observed that all 5 acceptable designs incorporate a nuclear propulsion system and all but 1 of them are at the “high” capability level. Additional insights can be derived by extending this analysis across multiple epochs as will be discussed in the following section.

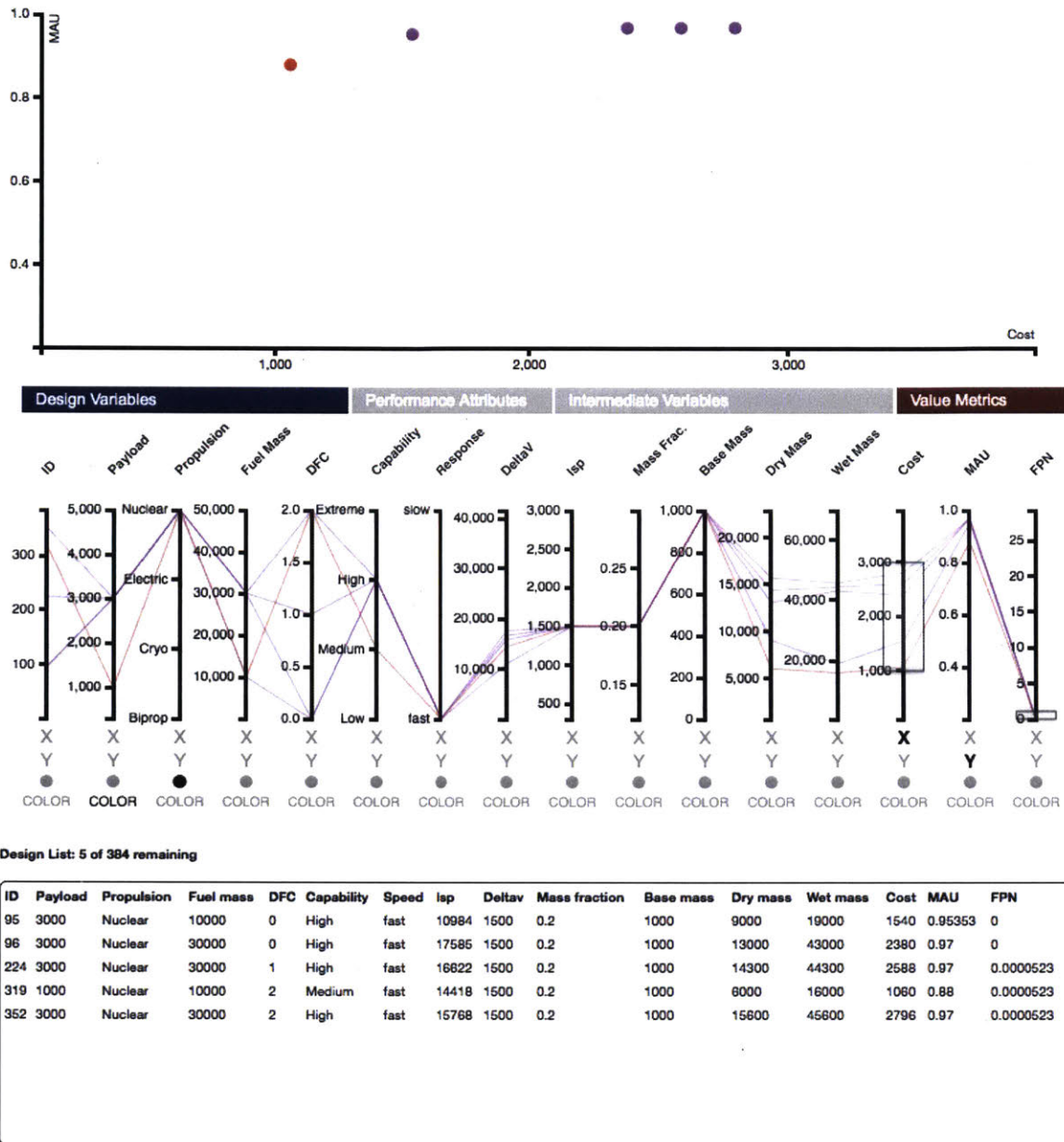


Figure 6-5: Filtered subset of alternatives in the baseline epoch (epoch 1)

6.4.2 Process 7: Multi-Epoch Analysis

The activities of process 7 allow a decision-maker to gain deeper insights by evaluating metrics between and across epochs to gauge the impact of uncertainties on system value. This includes the evaluation of short run passive and active strategies for achieving value sustainment such that systems can maintain value delivery across different missions or changing contexts. A system that is passively robust is insensitive to changing conditions and continues to deliver acceptable value. Alternatively, a system

that suffers deterioration in value due to evolving conditions may benefit from the use of change options that make them flexible, adaptable or resilient.

6.4.2.1 Evaluating passive strategies for value sustainment (Robustness)

Ideally a design alternative would be Pareto optimal in each of the 16 defined epochs and be within the required cost and performance constraints set by each stakeholder. This is often unrealistic, however, so a decision-maker may be required to settle for a design that is close enough to the Pareto front across most epochs. As was the case in process 6, “close enough” is operationalized through the FPN metric, but this analysis also must define a metric that captures the frequency at which a particular design meets a threshold FPN across epochs. To accomplish this, the Fuzzy Normalized Pareto Trace (FNPT) metric [46,30] is defined as the percentage of epochs in which a given design appears within a range from the Pareto front defined by the analyst. Applying these two metrics, a decision-maker can set a threshold FPN and evaluate how frequently a design appears close to the Pareto front across all epochs. Assuming no designs are Pareto optimal in every epoch, a decision-maker can choose to relax the acceptable distance from the Pareto front by increasing the FPN threshold or accept a lower FNPT indicating decreased Pareto efficiency of the design in some epochs.

As discussed in Chapter 4, one option for performing this type of analysis is to use an extended version of the single-epoch interactive application that allows design points to be tracked through epoch shifts. This provides the analyst with a natural extension of previous visualization and interaction techniques that could facilitate learnability of the interface. Starting off with the scatter plot visualization of epoch 1 as before, the analyst can now click on several points to mark them with a red “halo” so that they can be tracked through the epoch shifts. They can then use the drop down menu to select a new epoch and the points will move to their new location using an animated transition. Note that since the acquisition cost is the same across epochs only the MAU value for each point changes. This means that points only shift in the vertical (e.g. y-axis) direction. From Figure 6-6 it can be observed that several designs (30, 63, 95, 128) are Pareto optimal in epoch 1 and remain close to the Pareto front as the epochs shift. This pattern remains true across the 16 epochs, but only epochs 2 and 5 are shown in the figure as an example. Other designs that perform well in epoch 1 do not perform well in other epochs. Note for example how design 224 shifts away from the Pareto front in epoch 5.

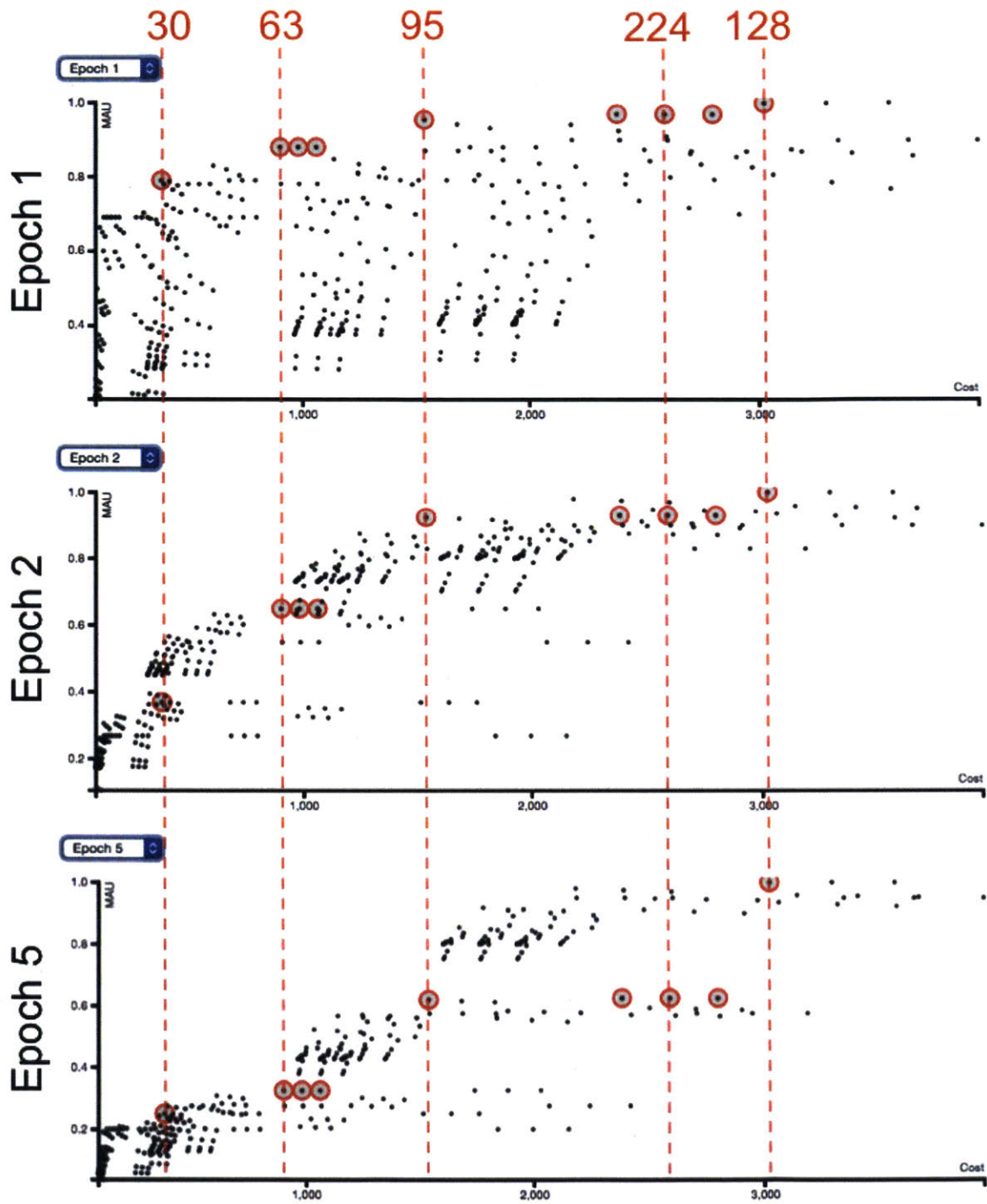
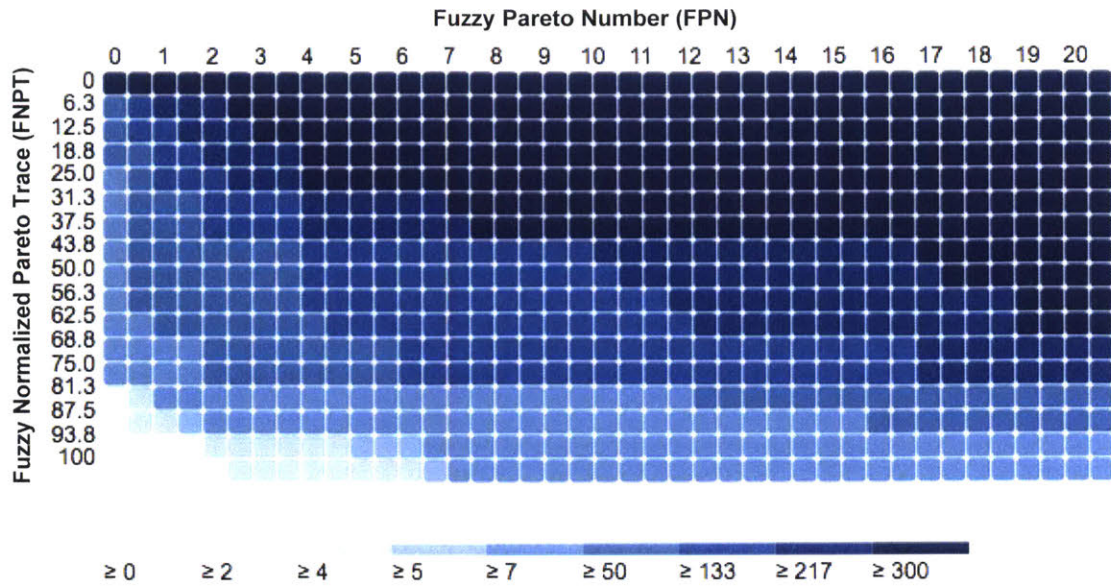


Figure 6-6: Design points tracked across epoch shifts (top) Epoch 1; (middle) Epoch 2; (bottom) Epoch 5

Using this type of interactive application is effective in many cases, but searching for the appropriate trade-off between FPN and FNPT can be a very manual process when performed this way. This approach can also become tedious or even impossible to use if the number of epochs is large as we will see in Chapter 7. This suggests that this analysis may benefit from a different type of implementation in an interactive application that better aggregates information for the analyst.

Binned aggregation techniques as discussed in Curry et al. [139] can be applied to overcome these types of issues. The interactive heatmap visualization in Figure 6-7 shows the tradeoff between FPN and FNPT using color to encode the number of designs that satisfy the threshold at each level. Clicking on any square in the heatmap brings up details on demand via a separate list of the designs that meet the cutoff. If an analyst would like to concurrently examine the impact of various FPN and FNPT trades on design and performance variables, a more complex visualization can be implemented using OLAP to handle issues that arise with more data dimensions and an increasingly larger data set that must be manipulated in real-time. As an example, the interactive visualization shown in Figure 6-8 applies OLAP, multiple coordinated views and binned aggregation to allow trade-offs between Pareto efficiency (FPN) and frequency of acceptable epoch performance (FNPT). This application also allows a decision-maker to determine not just the percentage of acceptable epochs, but also which epochs are most difficult for candidate designs. This is an insight not previously available or discussed in prior applications of multi-epoch analysis for this case study. These types of previously undiscovered relationships and patterns within the dataset may be useful for identifying “problem epochs” or when determining cases where it might be more appropriate to build a combination of systems to satisfy all possible future epochs.



Of 384 designs 5 are within 1.0% (fPN) of Pareto optimal in 87.5% (fNPT) of enumerated epochs.

Design ID#	Cost	Capability	Engine Propellant	Fuel Mass (kg)	DFC
30	382	Low	Nuclear	3000	0
63	900	Medium	Nuclear	10000	0
95	1540	High	Nuclear	10000	0
128	3020	Extreme	Nuclear	30000	0
191	980	Medium	Nuclear	10000	1

Figure 6-7: Interactive heatmap visualization

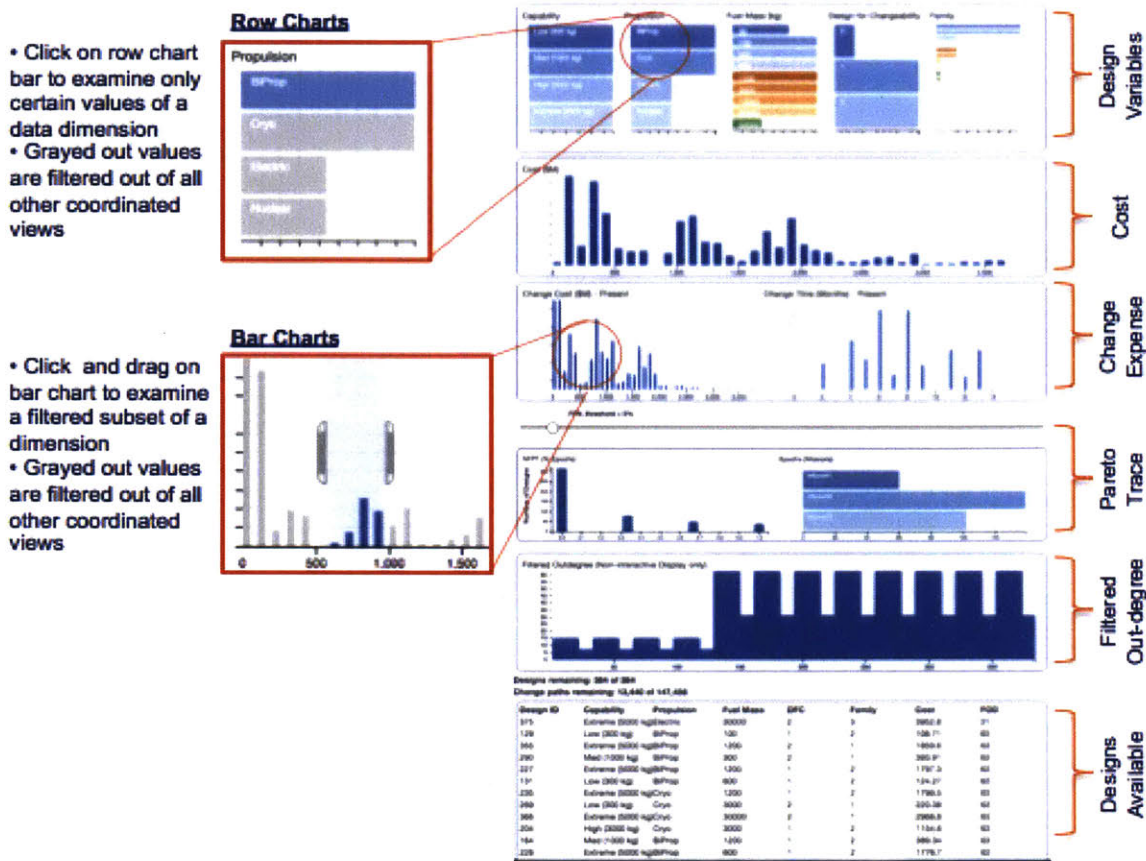


Figure 6-8: Interactive Filtering Application implementing OLAP

Applying this approach to the space tug case study it can be shown that none of the enumerated designs are Pareto optimal (FPN=0%) all of the time (FNPT=100%). Depending on the preferences of the decision-maker, using the interactive filtering application they could now choose to relax the FPN or the FNPT constraint to identify acceptable design compromises. Holding the requirement on Pareto efficiency (FPN=0%) constant and relaxing the requirement on FNPT it can be determined that 3 designs are Pareto optimal in 14 of 16 (FNPT=87.5%) of enumerated epochs as shown in Table 6-5. Alternatively, a decision-maker may be more willing to relax their requirement on Pareto efficiency (FPN=1%) and require that this threshold be met in all epochs (FNPT=100%) as shown in Table 6-6. Finally, if a decision-maker was willing to relax both the FPN and FNPT requirement more designs remain after interactively filtering as shown in Table 6-7. Comparing the designs identified here to those previously identified as passively robust by Fitzgerald [30], shown in Table 6-8, it can be observed that only 2 of the 5 designs are the same, designs 128 and 191. Notably, these two designs were later shown by Fitzgerald to be among the best performing of his selected designs in subsequent multi-epoch and multi-era analysis.

Table 6-5: 3 designs are within 0.0% (FPN) of Pareto optimal in 87.5% (FNPT) of enumerated epochs

Design#	Cost (\$M)	Capability	Engine Type	Propellant (kg)	Mass	DFC Level
63	900	Medium	Nuclear	10000		0
95	1540	High	Nuclear	10000		0
128	3020	Extreme	Nuclear	30000		0

Table 6-6: 3 designs are within 1.0% (FPN) of Pareto optimal in 100% (FNPT) of enumerated epochs

Design#	Cost (\$M)	Capability	Engine Type	Propellant (kg)	Mass	DFC Level
63	900	Medium	Nuclear	10000		0
128	3020	Extreme	Nuclear	30000		0
191	980	Medium	Nuclear	10000		1

Table 6-7: 5 are within 1.0% (FPN) of Pareto optimal in 87.5% (FNPT) of enumerated epochs

Design#	Cost (\$M)	Capability	Engine Type	Propellant (kg)	Mass	DFC Level
30	382	Low	Nuclear	3000		0
63	900	Medium	Nuclear	10000		0
95	1540	High	Nuclear	10000		0
128	3020	Extreme	Nuclear	30000		0
191	980	Medium	Nuclear	10000		1

Table 6-8: Passively robust designs identified by Fitzgerald [30]

Design#	Cost (\$M)	Capability	Engine Type	Propellant (kg)	Mass	DFC Level
1	97	Low	Biprop	30		0
29	306	Low	Nuke	1200		0
47	628	Low	Cryo	10000		0
128	3020	Extreme	Nuclear	30000		0
191	980	Medium	Nuclear	10000		1

6.4.2.2 Evaluating active strategies for value sustainment (Changeability)

The multi-epoch analysis metrics described above show how value sustainment through design robustness can be evaluated for this case study. A design that is not robust to changes in needs or context, however, may still be able to sustain value through the use of design change options. A system that is equipped with a design feature, or option, that allows it to change its state may do so to restore value if a future epoch is encountered that causes a loss of value. Typically, these change options are built into a design at the beginning of its life for an additional cost, but not used unless a particular future unfolds. There may also be an associated cost in money, time or other resources to execute the option. As described previously, a change strategy (e.g. maximize utility or efficiency) must also be defined to determine the conditions under which a change option should be used. For this case study, there are six change options defined as shown in Table 6-9. A logical series of questions that a decision-maker would want to answer next are: (1) Which of these options should be implemented to allow a candidate system to sustain value and what types of dynamic behaviors does this imply?; (2) What types of visualizations allow that to be assessed? (3) Are the options worth the cost?

Table 6-9: Available Change Options

No.	Change Option	Effect	DFC Level
1	Engine Swap	Biprop/Cryo swap	0
2	Fuel Tank Swap	Change fuel mass	0
3	Engine Swap (reduced cost)	Biprop/Cryo swap	1 or 2
4	Fuel Tank Swap (reduced cost)	Change fuel mass	1 or 2
5	Change Capability	Change Capability	1 or 2
6	Refuel in Orbit	Change fuel mass (no redesign)	2

These six change options allow a tradespace network to be constructed that shows how each starting design can be changed into other designs if the options are executed. Fitzgerald previously visualized the tradespace network using an adjacency matrix, but here the interactive force directed graph visualization, shown in Figure 6-9 was used. From visual inspection, it is clear that if we chose certain starting designs it will limit our ability to reach other designs later in the system’s lifecycle. Using metrics like FOD at this point might bias a decision-maker towards choosing a design within the largest “design families” which contain 64 designs. Exploring the tradespace network by changing the variable assignments of the visual elements offers interesting details, however that may also influence the designer’s decision. The example in Figure 6-9 shows how the visualization is updated when color and radius of the nodes are reassigned to the betweenness metric of the graph. Recall that the nodes that have a high degree of betweenness are ones that are frequently on the shortest path between other nodes. Three particular nodes (191, 224, 256) are highlighted in this example and can be shown to exhibit an interesting dynamic behavior in later era analysis. Specifically, the three designs exist within a steady-state limit cycle where they frequently change back and forth between one another as the era progresses.

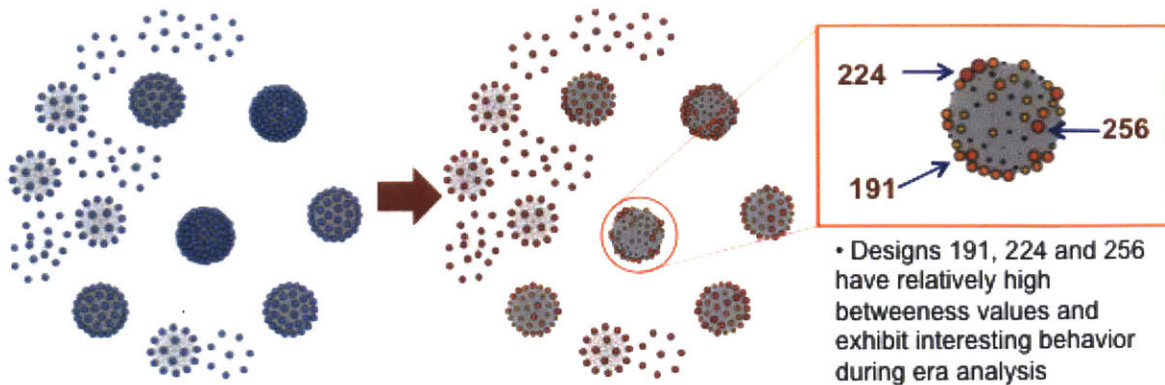


Figure 6-9: (a) Interactive force-directed graphs of change mechanisms between designs; (b) Betweenness centrality metric assigned to node radius

The value of a change mechanism to a given design will vary based on the strategy assumed. To evaluate the benefits of various strategies and change option pairs for a set of designs, two metrics, effective FPN (eFPN) and effective FNPT (eFNPT), can be used [30]. The eFPN and eFNPT metrics can be evaluated for a particular design across all epochs for each strategy. If the change strategy dictates that an original design change to a particular target design in a given epoch, then the target design is evaluated. If the change strategy dictates that a starting design does not change in that epoch, then that starting design is evaluated [29]. Assuming an operational strategy, the valuable changeability of enumerated designs can now be evaluated via the interactive application shown in Figure 6-9 or the updated version shown in Figure 6-10.



Figure 6-10: Multi-epoch analysis OLAP visualization with Nightingale coxcomb diagram

The interactive visualization shown in Figure 6-10 contains multiple coordinated views that can be illuminating here. The design and performance variable are represented by multiple bar charts and a slider allow the acceptable FPN threshold to be set which will update the chart. Also, in the upper right of the interface is a Nightingale coxcomb representation that summarizes the performance of designs within the current filter across various strategies. In this example, it compares the baseline (e.g. no change) strategy shown in dark blue to the strategy selected via the dropdown menu on the right, shown in light blue. Recall from Chapter 4 that the wedges of the coxcomb chart represent the enumerated epochs of which there are 16 in this case. Each wedge section represents two important pieces of information. The radial length of the wedge section represents the percentage of the current design alternatives that have satisfactory performance in that epoch. The arc length of each wedge section provides a measure of the average proximity to the Pareto front of the current design alternatives. This is represented by percentage above the FPN threshold set by the user (e.g. $[1-eFPN]/[1-FPN_threshold]$). A fully filled in wedge would therefore show the user that all of the remaining design alternatives are Pareto optimal in that particular epoch. A potential benefit of this visual representation is that it can give the analyst a holistic picture of not only which epochs are more difficult to satisfy, but also the gains they can expect by employing one strategy or another.

Continuing this analysis by following a similar approach to the one described by Fitzgerald, some interesting behaviors can be observed in the data. Assuming an acceptable FPN threshold of 5% and a maximize efficiency strategy, gains can be observed in all 16 epochs in terms of both yield and average eFPN. Examining the

details of epoch 5, as shown in Figure 6-11, shows an increase in yield from 85% to 100%, meaning all designs under consideration can now satisfy epoch 5 at the 5% FPN threshold relying on either robustness or changeability. If the assumed strategy is changed to the maximize utility strategy, similar gains in yield can be observed across all epochs, but gains in eFPN are less significant than in the maximize efficiency strategy. This makes sense because occasionally the maximize utility strategy will lead to cases where a design will change to a higher performance design that is less cost effective, leading to a lower Pareto efficiency.

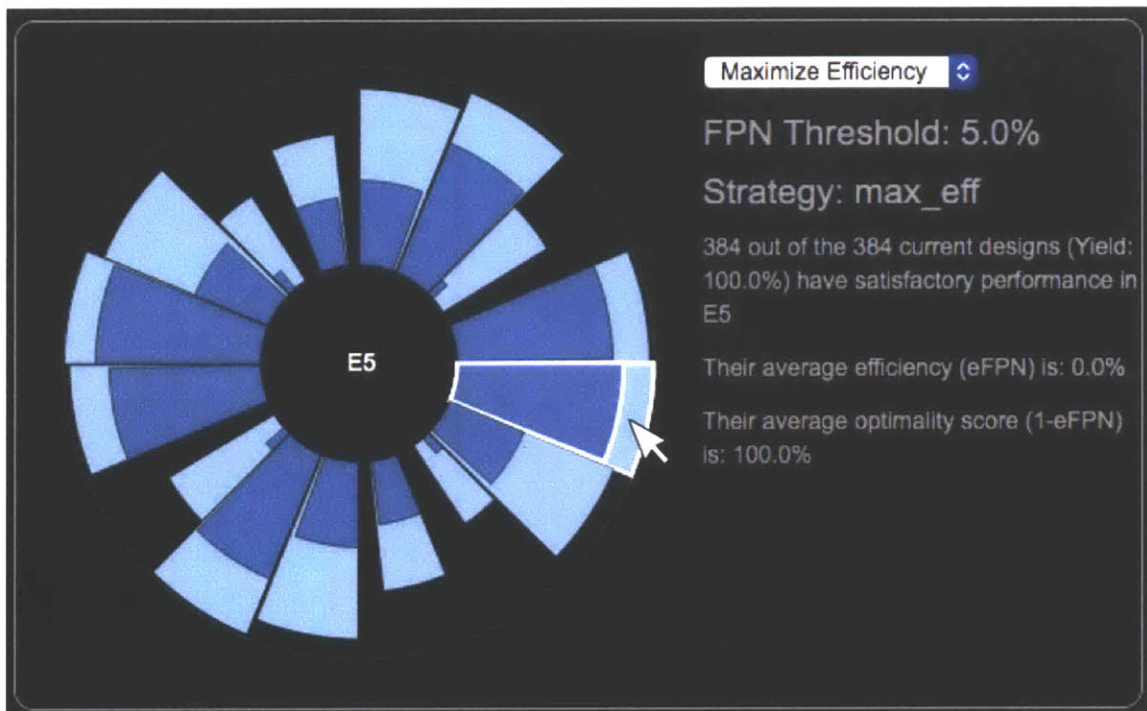


Figure 6-11: Nightingale coxcomb (“rose”) visualization

Looking at the data at this high level might lead an analyst to the conclusion that adding changeability is generally a good thing. However, when the design space is filtered to include only those designs with an eFNPT greater than 90% as shown in Figure 6-12, it can be observed that this smaller set of designs relies less on changeability to maintain value. This makes sense because these designs are for the most part passively robust to change. Depending on the particular preferences of a decision maker or analyst, they may choose to examine different filtered subsets of the data and different strategies to find the designs most interesting to them to be carried forward in the IEEA framework for further scrutiny. Also, though not shown in this example, rule removal studies as proposed by Fitzgerald [30], could also be implemented in this interactive application to allow a decision-maker to develop intuition regarding the value to a system of having a particular change options. These have been omitted from the current discussion for brevity.

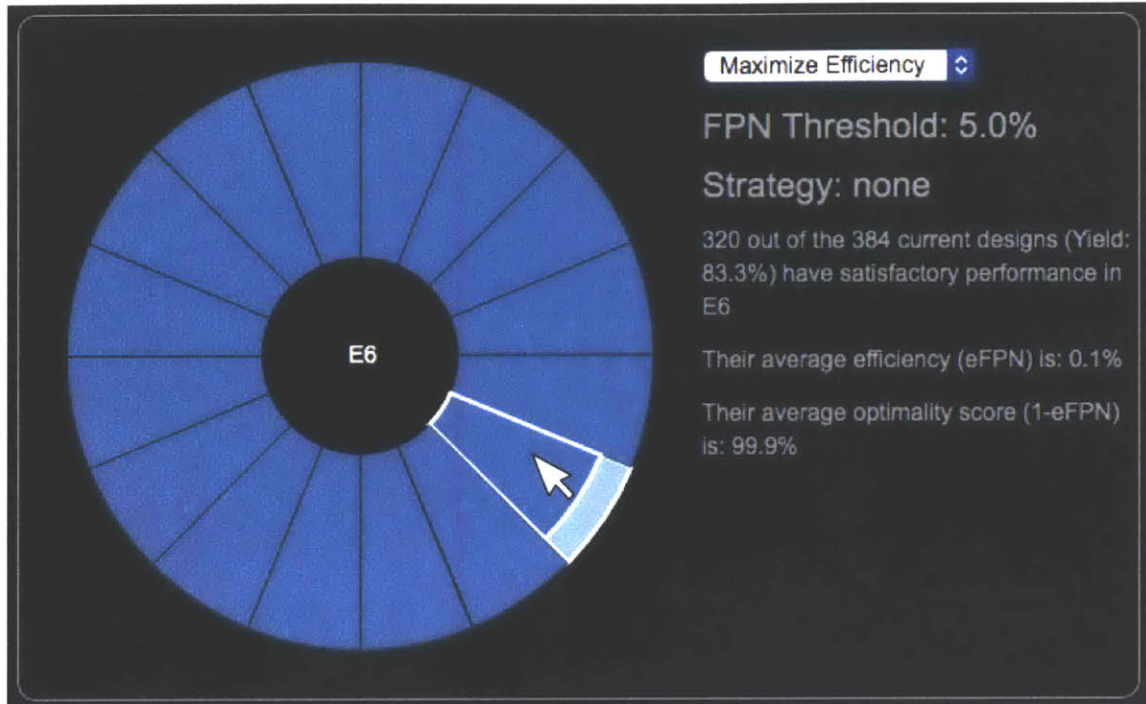


Figure 6-12: Filtered subset of passively robust designs

6.4.2.3 Summary of Multi-Epoch Analysis

The analyses outlined in this section provide an example of the different ways analysts and decision makers can interactively evaluate the performance of multiple design alternatives across multiple futures. This creates opportunities for new insights at the expense of a potentially large and complex data set that can be difficult to make sense of even for this simplified case study. The application of the IEEA framework and interactive applications allows the user to visualize and engage with the data in new ways that may facilitate improved comprehension and decision-making. The insights that can be extracted from this approach allow the decision-maker to understand the characteristics of designs that can sustain value in all possible futures through passive robustness or active changeability.

6.4.3 Process 8: Single-Era Analyses

Epoch-analysis is focused on the evaluation of short run passive and active strategies for achieving value sustainment. In contrast, era-analysis focuses on long run sustainment of system value delivery across different missions or changing contexts. This process examines the time-dependent effects of an unfolding sequence of future epochs created in Process 4. By examining a particular series of epochs for a given length of time, decision-makers can identify potential strengths and weaknesses of a design and better understand the potential impact of path-dependent and time-dependent, long run strategies for value sustainment.

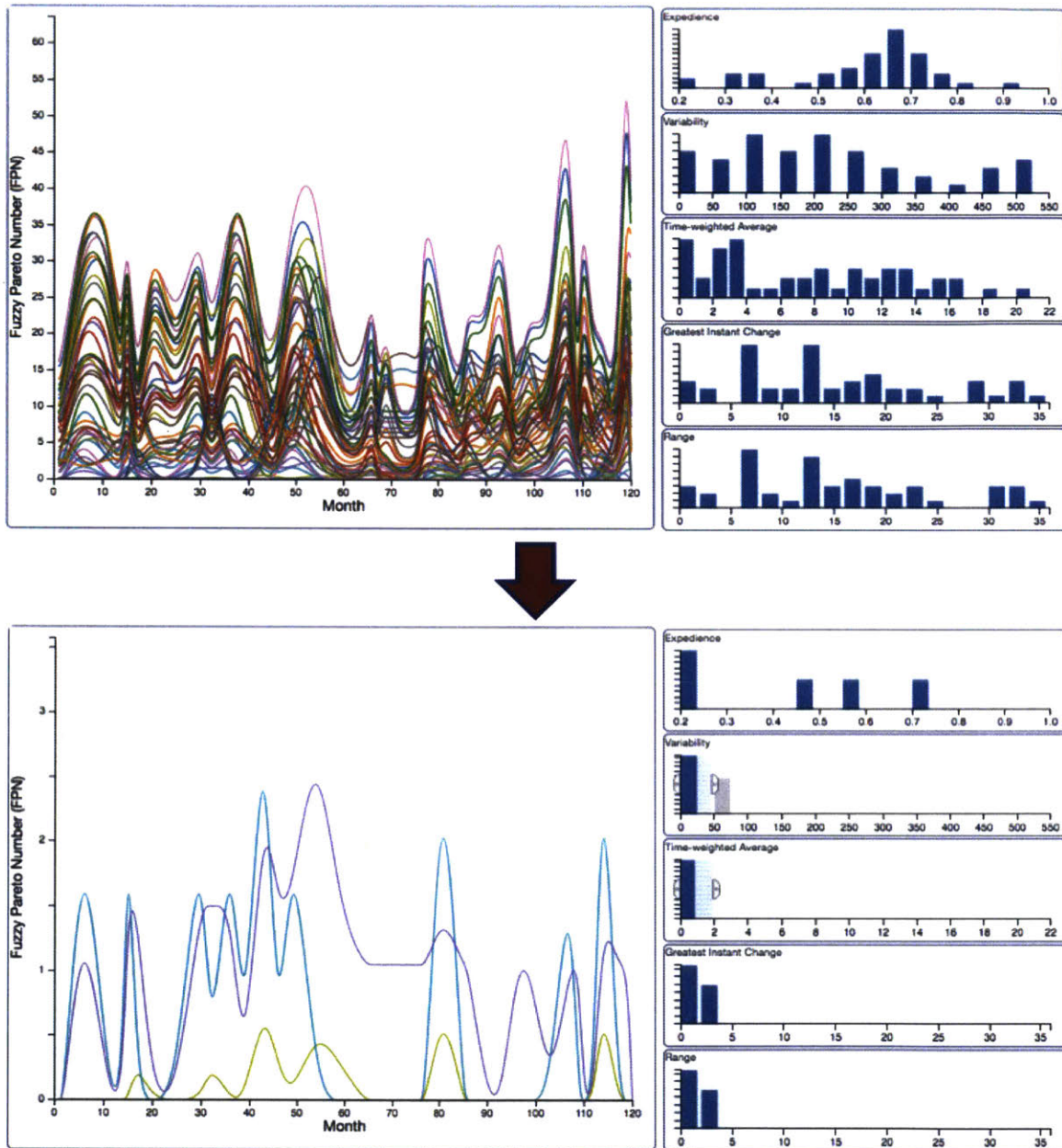


Figure 6-13: Interactive application showing candidate designs across a single era (a) before filtering; and (b) after

As demonstrated for previous IEEEA processes, decision-making in single-era analysis can also benefit from the application of techniques such as multiple coordinated views, interactive filtering and OLAP. An example application, shown in Figure 6-13, shows the FPN performance of all designs across time for a specified era and era-level strategy. The five histograms to the right display aggregated data on the performance of the candidate designs for the era metrics identified by Schaffner [29]. These era-level metrics use eFPN as the metric of interest (MOI) and are defined as follows:

1. **Expedience** – the percentage of the MOI’s total value that is delivered in the first half of the era.
2. **Variability** – the stability of the MOI over the era.
3. **Time-weight average** – the average value of the MOI over the era.
4. **Greatest instant change** – captures the largest difference in the MOI between any two consecutive time steps.
5. **Range** – captures the difference between the minimum and maximum of the MOI.

Interactive filtering on these metrics allows a decision-maker to rapidly identify interesting designs based on their individual preferences for average performance and stability of performance across time. It also gives them a way to better comprehend design behavior that has not previously been demonstrated. In this example, the data has been filtered to find the designs that have a low average FPN and low volatility. These designs will remain close to the Pareto front throughout the era.

This example is intentionally simplified to more clearly demonstrate how single era analysis can be aided by an interactive application. As will be shown in the second case study of this thesis, this example could be expanded upon to allow more detailed analysis. For instance, several eras and strategies can be visualized simultaneously and coordinated views can be added to allow filtering of these additional eras and strategies. More metrics of interest can also be added beyond simply Pareto efficiency over time. Examples of how this can be used to explore a more complex case will be provided in the next chapter.

6.4.4 Process 9: Multi-Era Analysis

This process extends Process 8 by evaluating the dynamic properties of systems across many possible future eras, identifying patterns of strategies that enable value sustainment across uncertain long run scenarios. When looking at only a single era it is more feasible to compare how individual designs perform relative to one another using the era metrics previously discussed that capture temporal aspects of value delivery. This is not always practical when analyzing many possible eras. In fact, it has been previously shown that it would be impossible to characterize the entire era-space for even some simple case studies [29,139]. The goal then for multi-era analysis is focused more on understanding the aggregate behavior of designs given different long-run strategies for operating a system. Specifically, it is useful to better understand any possible path dependencies that may arise due to either external perturbations/shifts or the application of operational strategies that define usage rules for available design change options.

In past research on path-dependency analysis for multiple eras, the progression of epochs within an era has been modeled as a directed acyclic graph² or tree of events [29,36,162]. This is similar to how path-dependency analysis is conducted in programs that analyze strategy games such as tic-tac-toe where the decision tree is searched using variants of the minimax algorithm to determine the best move at each step. In more complex games, such as chess, partial tree searches are typically required to keep the problem computationally tractable and the decision approaches optimal with increasing depth of the search through the tree³ [163]. HIL interaction, however, can be leveraged to enable the decision tree to be searched more efficiently. The benefits of HIL interaction has been demonstrated on related path-analysis problems such as the traveling salesman problem [140] and “human-machine” chess matches that demonstrated a human player, coupled with chess software, can fairly consistently beat computer-only players [6]. This suggests that multi-era path analysis could also benefit from the right combination of interactive applications that leverage the experience of subject matter experts (SME) to identify beneficial or detrimental path-dependencies within eras.

As an example of how interactive multi-era analysis can generate insights into system behavior and long-run value delivery we can look at path dependencies that arise due to changeability usage for the space tug case study. As shown in Figure 6-14, the chord diagram can be used to represent the proportion of the time that a source design executes a change option to reach various target designs across multiple eras. All the designs that use change options to sustain value are enumerated around the circumference of the diagram and quadratic Bézier curves show the proportion of each source design changing to each target. The source and target arcs represent mirrored subsets of aggregate change behavior. Detailed analysis using this visualization allows an analyst to quickly identify designs that rely on changeability (rather than robustness) to maintain value and which options and end-state designs that are frequently used for various strategies.

² Note that eras could also be modeled using a directed cyclic graph. For instance, if Markov Chain Monte Carlo (MCMC) methods were applied and transitions between a finite number of defined epochs were modeled probabilistically as was attempted by Fulcoly (2012).

³ The exception is so called “pathological” game trees (Nau, 1983).

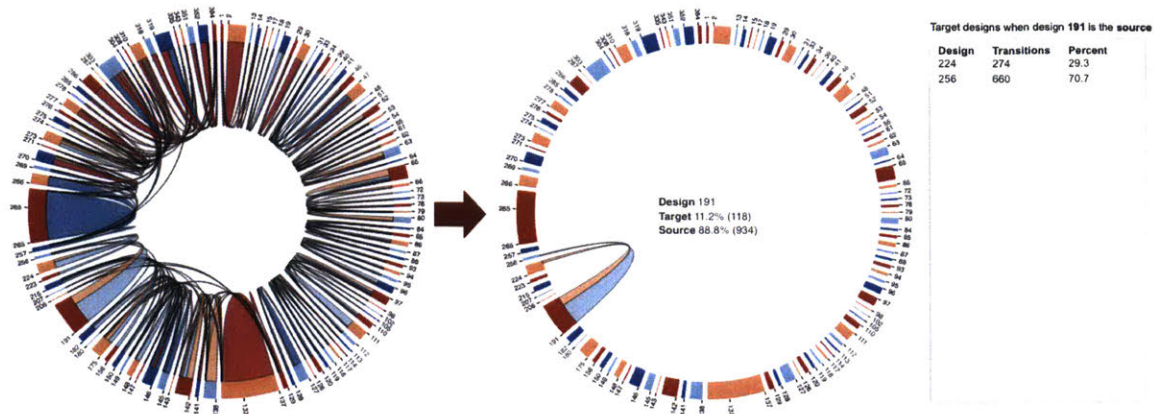


Figure 6-14: Interactive chord diagram used to visualize design change behavior.

The multi-era change path dependency analysis shows that while the network of changes (due to execution of options) that manifest during the space tug analysis are complex, interaction can allow specific insights to be extracted. For example, from the interactive chord diagram visualization shown in Figure 6-14 we see that only a small fraction of designs, 109 out of 384 (28%), actually use changeability to maintain value when implementing the multi-era maximize efficiency strategy. By hovering over a specific design we can gain more detailed information about its behavior across eras. Clicking on a particular design displays interactive text in the center of the chord diagram that provides details on how frequently the design is the target or the source. To bring up additional details, a user can click on the “source” or “target” text in the center to get a more detailed list of the linked designs. In this example, design 191 is shown to exist in a change “limit cycle” with designs 224 and 256. When executing a change option design 191 will change 29% of the time into design 224 and 71% of the time into design 256. We can also observe from this interactive visualization that design 191 is the target end state rather than the source design 8 times less frequently. When it is the end state, design 224 is the source 66% of the time and 256 the remainder of the time. That these 3 designs never transition to any of the other designs within their reachable network (community), which contains 32 total designs, highlights their relative importance in this strategy. This behavior can be shown to vary significantly with the strategy assumed. This emphasizes the point that system value delivery is sensitive not only to variables related to design, change options and context, but also to operational characteristics that must be considered.

6.5 Decision-Making

The following subsections describe the processes of the decision-making module of IEEA.

6.5.1 Process 10: Decisions and Knowledge Capture

The purpose of this process is not only to capture the final decision that is made, but also the chain of evidence that led to that decision which can be captured in a database or other knowledge management system. This information may prove useful to future studies by allowing post-hoc analysis of the rationale and specific assumptions that went into a decision. Though not demonstrated in detail for this case study, the capability to capture and store key information about the reasoning behind a decision is an advantage of implementing IEEA in integrated applications such as the web-based application demonstrated here. Many of the data management capabilities described in Chapter 3 can be incorporated here to systematically collect information about the design process as it progresses so that that information can be used in future studies.

7.0 Case Study 2 – Commercial offshore ships

The space tug case study described in Chapter 6 provided an example for how the IEEA framework could be applied in detail to a simple, but non-trivial, system design problem. Though the problem was a familiar one studied in prior research [30] interactive visualizations allowed the discovery of new insights that can impact previous conclusions. As a next step, this chapter explores the application of IEEA to a new problem domain and examines issues related to scalability of both the framework and interactive visualization applications. Issues related to scalability can derive from four primary aspects, depending on the nature of a particular case study [77]:

1. Amount of data
2. Dimensionality of data
3. Complexity of data
4. Dynamic data

Though the system model considered for this case study is of greater complexity, scalability as illustrated in this chapter will primarily center on issues that arise due to the quantity and dimensionality of the data. This chapter applies the IEEA framework to a case study focused on commercial offshore ship design, incorporating interactive visualizations, similar to those shown in the previous case study, to gain insight from large, high-dimensional data sets to facilitate improved strategies for value sustainment. The application of IEEA to this problem is motivated by a need to address design questions that are not well-suited for analysis solely with metrics, often applied in other EEA case studies, such as fuzzy Pareto number (FPN) or fuzzy normalized Pareto trace (fNPT). For the offshore ship design case, this includes assessing the trade-off between designs optimized to target the primary mission versus being robust for uncertain subsequent missions. This case study is based on the one described by Rehn et al. [164]. A basic description of the case is provided throughout this chapter, but the reader is referred to the paper by Rehn et al. for a more detailed discussion of the case setup.

7.1 Case Background

Offshore ships, in contrast to traditional deep-sea cargo ships, are designed to provide special operational services typically related to the offshore oil and gas industry. This group of ships comprises platform supply vessels (PSV), inspection maintenance and repair (IMR) and offshore construction vessels (OCV), to mention a few. A recent period of high oil prices and deep sea petroleum discoveries has spurred the development of offshore oil and gas fields. As a result, there has been a growing need for offshore services, including well maintenance and intervention services with light, riserless technologies. OCVs have taken an increasingly large part in the development of these, in particular for the marginal fields, due to their price competitiveness. Additionally, the Deepwater Horizon oil spill in 2010 in the Gulf of Mexico has changed some of the focus

for the offshore ship owners towards being able to provide various deepwater emergency and rescue operations. This strong market period has characteristically driven the design of offshore ships towards multifunctional, “gold-plated” and expensive solutions [165]. However, the recent oil price collapse of 2014 has had a significant impact on the offshore markets, rendering many of these multifunctional ships less competitive against cheaper, specialized ships. The current situation in the offshore industry serves as a good example of the importance of focusing on value robustness and operational flexibility as key factors for success in a highly volatile maritime industry [166,167].

Offshore ships are usually built either for a specific long-term contract or on speculation. A long-term contract may last 5-10 years, and these ships are often specialized for the particular mission. Ships built on speculation tend to be more multifunctional, to be able to take on different contracts. If these ships do not get any lucrative long-term contracts, they are often offered in the spot market to take on various short-term contracts. If a ship does not get a contract, it is idle for short periods or laid up over longer periods. This case study motivates several questions, the evaluation of which may be aided using interactive applications described in this thesis and by prior IEEA case studies:

1. What is the trade-off between optimizing for the primary contract and making the design robust to more than one contract in terms of the number of acceptable designs in the tradespace?
2. What is the impact in terms of both cost and reduced performance when attempting to ensure that designs satisfy all potential contracts?
3. What are the benefits and drawbacks of active versus passive value robustness?
4. Which contracts (e.g. epochs) are most challenging to satisfy?

7.2 Elicitation

The following subsections describe the processes of the elicitation module of IEEA.

7.2.1 Process 1: Value-Driving Context Definition

The first process defines the stakeholders, problem statement, exogenous uncertainties and the basic value proposition for the system. For this case, the business opportunity for a new offshore ship design emerges from an expected strong demand for offshore oil and gas over the next couple of decades, despite recent short-term oil price volatility. The Deepwater Horizon accident has further resulted in an increased focus on being able to provide advanced offshore emergency services in the Gulf of Mexico. An offshore ship owner wants to target this business opportunity, and, in particular, a potential five-year contract for a large oil company. The ship owner values a solution that is both profitable and environmentally conscientious (e.g. eco-friendly).

7.2.2 Process 2: Value-Driven Design Formulation

The second process begins by defining the statements of needs, which become the attributes of system performance; along with utility functions describing the preference for each attribute. The system boundary for the single ship design is around the ship itself and does not consider, for example, the total profitability of the overall shipping company. Profitability is a measure of the ability of the design to generate profits, and eco-friendliness represents the ability of a design to reduce emissions during operation and transit. The non-monetary and monetary value attributes are kept separate due to their temporal differences in the model, which is further discussed in Rehn et al. [164]. In the model, profitability is considered at the era level, while eco-friendliness is considered at the epoch level.

Even though value focused thinking involves exploring various high-level solution forms, the form of a standard single-hull OCV is assumed for demonstration purposes in this case study. The following ship-level design variables are considered: length, beam, depth, power, accommodation, main crane, light well intervention tower, moonpool, fuel type, dynamic positioning, remotely operated vehicle (ROV), pipe laying capability and design for changeability level.

7.3 Generation / Sampling

The following subsections describe the processes of the generation and sampling modules of IEEA.

7.3.1 Process 3: Epoch Characterization

In process 3, the key contextual uncertainties are identified so that epoch variables can be characterized. Based on the system boundary defined, eight epoch variables are identified, as illustrated in Figure 7-1 and described in Table 7-1. These epoch variables represent the details of a missions for a ship, operationalized through the contract type, technical requirements, and operational area. The contract type implies the rate (K\$/day) that can be earned by the ship if the contract is accepted. The technical requirements are driven by which one of the 12 missions shown in Table 7-3 is associated with the contract. The contract also specifies one of four operational areas which each impose different requirements on what sea state and water depth the ship must be able to handle as shown in Table 7-3.

Contract

- Rate [kUSD/day]
- Requirements
 - Light well int. [tonnes]
 - Subsea module [tonnes]
 - Accommodation [POB]
 - Remotely operated vehicle
 - Deck area [m]



Operational area

- Gulf of Mexico
- North Sea
- Brazil
- West Africa

Area information:

- Sea state (Hs) [m]
- Water depth [m]

Figure 7-1: System boundaries and epoch variables [164].

Table 7-1: Epoch variables [164]

	Epoch Variable	Unit	Values
Contract Parameters	Contract Type	[-]	[Spot, Term]
	Operational area	[-]	[Gulf of Mexico, Brazil, North Sea, West Africa]
Technical Requirements	Light well intervention requirement	tonnes	[0, 300, 600]
	Module weight req.	tonnes	[0, 200, 400, 600]
	Accommodation req.	POB	[50, 150, 250, 350]
	ROV requirement	[-]	[0, 1]
	Dynamic positioning requirement	[-]	[0, 1]
	Deck area req.	m ²	[0, 1000]

Table 7-2: Missions associated with technical requirements [168]

Mission
Subsea installation & Construction
Inspection, maintenance and repair
Light well intervention
Offshore accommodation
Offshore cable laying
Offshore pipe laying
Offshore platform supply
Emergency response
Offshore mining support
Offshore aquaculture support
Field decommission support
Offshore wind support

Table 7-3: Operational area requirements [164,168]

Operational Area	Depth requirement (m)	Wave height requirement (m)
Gulf of Mexico	1600	2.0
Brazil	2500	2.5
North Sea	200	3.0
West Africa	1800	1.0

7.3.2 Process 4: Era Construction

This process constructs era timelines composed of multiple sequences of epochs each with a set duration to create long-run descriptions of possible future scenarios a system may encounter. Simulating lifecycle performance in this way allows an analyst to evaluate path-dependent effects that may only arise when uncertainty is time-ordered. The activities in this process are in many ways analogous to those used in narrative or computational scenario planning. The future timelines can be constructed manually with the aid of expert opinion (narrative) or by implementing probabilistic models (computational), such as Monte Carlo simulation or Markov chain models that define epoch transitions.

Three narrative scenarios are considered in this case study. The intent is to capture some insights regarding the volatility of the oil market by having eras corresponding to rising, flat and declining oil prices, respectively. In two of the eras the ship gets the targeted five-year contract initially, and experiences a relatively strong market the rest of the assumed 20-year lifetime. In the third era, the ship does not get the targeted contract due to a market collapse. The three areas, described by their technical requirements, contract rates, operational area and mission type, are shown in Figure 7-2. Each epoch is assumed for simplicity to have a fixed duration of one year. Rehn et al. [164] describe the three eras as follows:

- 1. Era 1 represents a baseline scenario, with the initial targeted tender and a strong offshore market continuation.*
- 2. Era 2 represents a similar start with the targeted tender, followed by a weakened market that ends with offshore decommissioning in the later years of the lifecycle.*
- 3. Era 3 represents a market collapse, where the initial targeted contract is not won.*

Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
ERA I	Region	GoM	GoM	GoM	GoM	GoM	Bra	Bra	NS	NS	NS	NS	NS	WA	Bra	Bra	Bra	GoM	GoM	GoM	GoM
	Operation	LWI	LWI	LWI	LWI	LWI	Sub	Sub	LWI	LWI	LWI	LWI	LWI	ER	Sub	Sub	Sub	Acc	Acc	Acc	Acc
	Dayrate																				
	Tech. Requi.																				
ERA II	Region	GoM	GoM	GoM	GoM	GoM	Bra	Bra	Bra	Bra	GoM	GoM	GoM	NS	NS	NS	NS	NS	NS	NS	NS
	Operation	LWI	LWI	LWI	LWI	LWI	Sub	LWI	LWI	Sub	Sub	Acc	Acc	Acc	Sub	Sub	Sub	LWI	LWI	LWI	LWI
	Dayrate																				
	Tech. Requi.																				
ERA III	Region	NS	NS	NS	NS	NS	NS	WA	WA	WA	WA	WA	WA	WA	NS	NS	NS	NS	NS	NS	NS
	Operation	X	Sub	LWI	LWI	Sub	Sub	X	Sub	Sub	Sub	Acc	Acc	Acc	Acc	Sub	Sub	LWI	LWI	LWI	LWI
	Dayrate																				
	Tech. Requi.																				

Operational area		Type of operation		Dayrate		Tech. Requirements	
GoM	Gulf of Mexico	Sub	Subsea installation		Very low		Low
Bra	Brazil	LWI	Light Well Intervention		Low		Medium
NS	North Sea	Acc	Accommodation		Medium		High
WA	West Africa	ER	Emergency response		High		Very high
		X	No contract (Idle)		Very high		

Figure 7-2: Descriptions of 3 narrative eras [164,168]

7.4 Evaluation

The following subsections describe the processes of the evaluation module of IEEA.

7.4.1 Process 5: Design-Epoch-Era Evaluation

As was done before with the space tug case study, in this process step the previously defined models are integrated to map design and epoch variables into stakeholder benefit and expense. For the offshore ship, the various key performance indicators are estimated based on an integrated performance model that maps the design variables to the performance attributes, including speed, deck area, dead weight, and eco-friendliness score. Expense attributes, including acquisition cost and operational costs, are estimated in a similar manner. The design variables and levels considered in this analysis are shown in Table 7-4. A full enumeration of the design space would yield 124,416 designs, but not all design variable permutations are considered feasible. A component compatibility matrix is used to cull some designs from the full factorial enumeration of the design space resulting in 41,024 designs that are feasible within at least one epoch. Furthermore, during epoch analysis, designs that violate the technical requirements in an epoch are rendered invalid within that particular epoch.

Table 7-4: Design variable levels [164,168]

Design Variable	Levels
Length (m)	120, 150, 180
Beam (m)	20, 25, 30
Depth (m)	8, 13
Installed power (MW)	15, 25
Accommodation (persons)	50, 250, 400
Main crane capacity (tonnes)	0, 400, 800
Light well intervention (tonnes)	0, 300, 600
Moonpool	No, Yes
Fuel type	Marine Gas Oil, Dual Fuel
Dynamic positioning capability	DP2, DP3
Remotely operated vehicle	No, Yes
Pipe/cable laying equipment	No, Yes
Design for changeability level	0, 1, 2, 3

Table 7-5: Performance attribute levels across all evaluated designs

Performance Attributes	Range
Maximum Speed (knots)	[15.8, 24.4]
Deck Area (m ²)	[20.7, 3032.3]
Dead Weight (tonnes)	[4127.6, 30155.0]
Eco-friendliness score	[0, 10]

Table 7-6: Expense attribute levels across all evaluated design

Expense Attributes	Range
Acquisition cost (\$M)	[86.8, 416.1]
Operational cost (\$M/yr)	[20, 500]

The epochs for this case study are based on the available contracts. As described in section 7.3.1 the contract definition is comprised of its type, operational area and mission. Therefore, there are 2 (contract types) * 4 (operational areas) * 12 (missions) = 96 possible epochs. The epoch space is considerably larger than the one previously described for the space tug case study which imposes some data management and transformation challenges. To consider the feasibility and value delivery of all possible design-epoch pairs a total of 41,024 (designs) * 96 (epochs) \approx 4 million evaluations are necessary. The scale of the data required for this case study creates unique challenges, but the analysis using interactive applications is similar in many ways to what was demonstrated for the space tug case study. The following sections will discuss the analysis of this case in further detail.

7.5 Analysis

The following subsections describe the processes of the analysis module of IEEA.

7.5.1 Process 6: Single Epoch Analyses

As was done earlier in this thesis with the space tug case study, the analysis of the ship case begins with single epoch analysis. Figure 7-3 illustrates the tradespace for the primary contract for the offshore ship design base case, that is the targeted contract with no technical requirements (e.g. epoch 1). At this stage, an analyst can focus on understanding the dynamics of the underlying system. In this particular case study, the MAU function is only comprised of one single attribute utility function, that is eco-friendliness, even though the figure indicates a multi-attribute utility function on a general basis. The interactive filtering can aid in visualizing the exploration process and understanding the relative significance of individual design variables, as illustrated. For instance, filtering by beam and length, an analyst can see that relatively slender ships tend to contribute to low FPN values which indicate designs that are near-optimal. However, this again makes a design less stable in the water, which restricts the possibilities of retrofitting heavy equipment on deck without intervening with the main hull. Further, one can directly see the trade-offs of adding DFC levels, as design points shift right in the tradespace with increasing DFC due to increased cost.

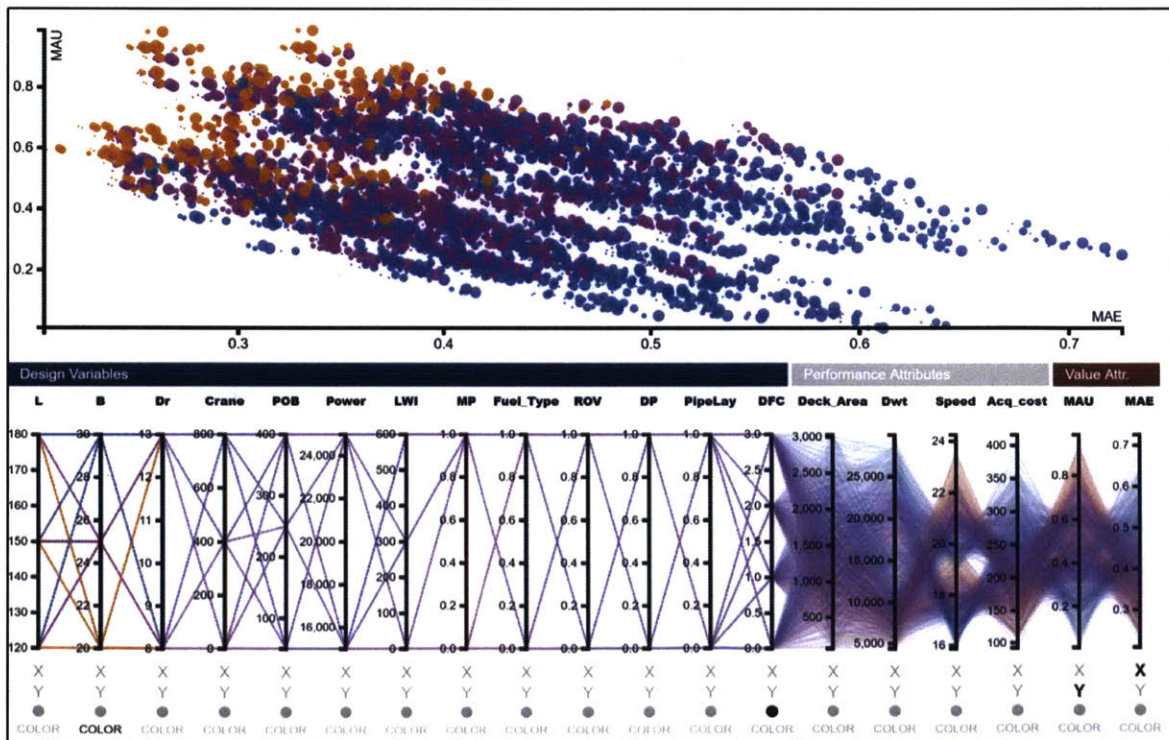


Figure 7-3: Interactive Filtering Application for tradespace exploration for the offshore ship design base case

This case study enumerates over 40,000 design alternatives, which means the number of elements that must be rendered and manipulated on the screen is increased by approximately two orders of magnitude when compared to the space tug case described in Chapter 6. Unlike the prior case study, this case has more designs than can feasibly be plotted in the scatter plot without running into issues with visual occlusion due to overlapping points. Furthermore, the large number of elements can lead to latency issues due to memory and processing limitations when the analyst attempts to filter or manipulate the data in any way. Latency issues due to data transmission also occur when the visualization is initially loaded into the browser because of the large amount of data that must be pulled from a flat file or database.

Recall the observation made by Liu et al. that “perceptual and interactive scalability should be limited by the chosen resolution of the visualized data, not the number of records,”[65]. This suggests that a properly conceived interactive application should not be limited by the large number of designs considered in this case, but rather only by the level of granularity at which an analyst needs to perceive the data in order to comprehend it. Several of the methods described in Chapter 3, including filtering, sampling or binned aggregation, can be applied in this case to enable scalability of the single epoch interactive visualization application by reducing the resolution of the visualized data. Pre-filtering or sampling the data would be an easily implemented solution, but come with the downside of potentially concealing important data points. However, applying a two-dimensional binned aggregation approach would allow a reduction in the number of visual elements that must be plotted to the screen without losing any information. Shown in Figure 7-4, an example visualization that uses hexagonal bins to display the same information previously shown in Figure 7-3 can reduce the number of visual elements that must be rendered by a factor of 10 (approx. 4000 bins instead of 40,000 points). In this example bin color is used to encode information about the spatial density of design alternatives rather than plotting every single point. By controlling the bin size the analyst can effectively control the resolution at which they would like to visualize the data regardless of the number of data points. For example, the visualization shown in Figure 7-5 increases the size of the bins, which results in a further reduction in the number of visual elements by an additional factor of 5 (approx. 800 bins). Adjusting bin size in this way allows the analyst to control the resolution at which they would like to examine the data and scale their analysis relative to the amount of computational resources available to them. Note that while not implemented for this case study, related approaches could also be applied to visually scale the parallel coordinates plot. Approaches for doing so are discussed in Appendix 9.4.

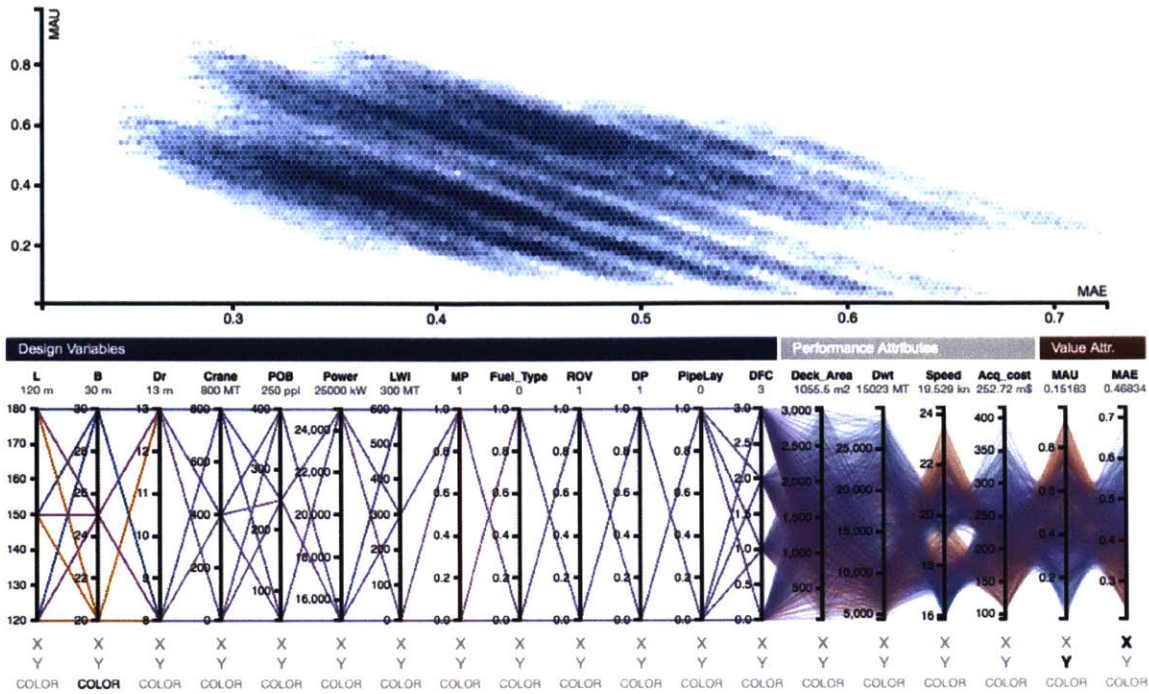


Figure 7-4: Interactive Filtering Application with (fine) hexagonal binning

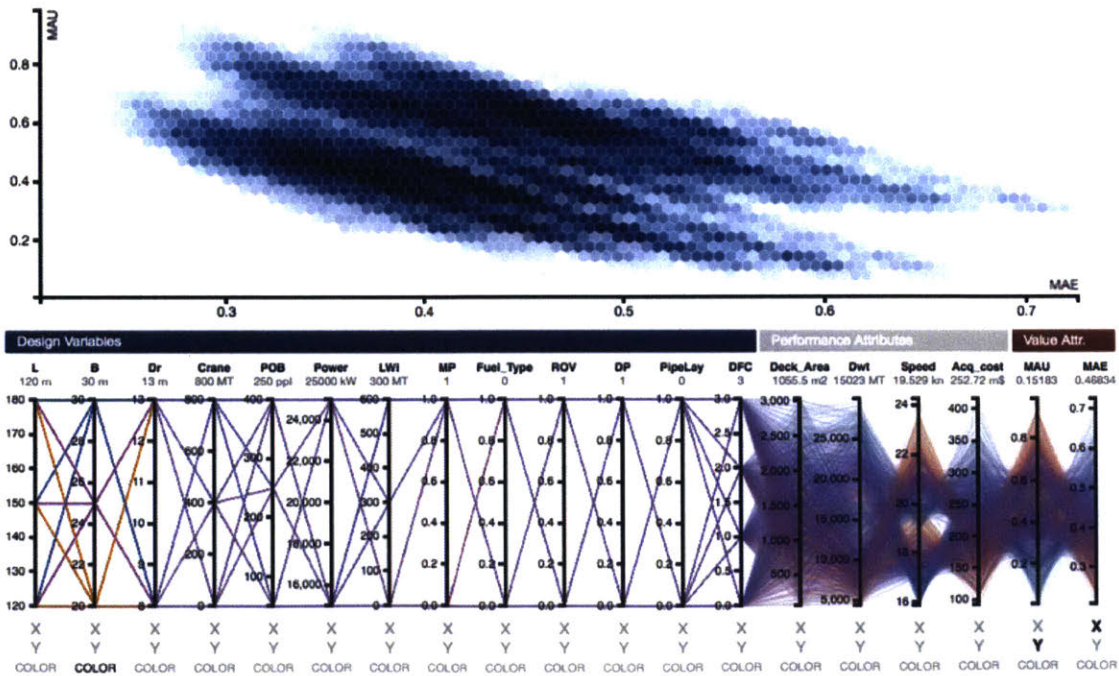


Figure 7-5: Interactive Filtering Application with (course) hexagonal binning

7.5.2 Process 7: Multi-Epoch Analysis

The activities of process 7 allow decision-makers to gain deeper insights by evaluating metrics between and across epochs to gauge the impact of uncertainties on system value. This includes the evaluation of short run passive and active strategies for achieving value sustainment such that systems can maintain value delivery across different missions or changing contexts. A system that is passively robust is insensitive to changing conditions and continues to deliver acceptable value. Alternatively, a system that suffers deterioration in value due to evolving conditions may benefit from the use of change options that make it flexible, adaptable, or resilient. Because multi-epoch analysis must by definition consider a larger amount of data issues with scalability of interactive application can be more apparent. For the analysis discussed in this section, a much larger number of designs and epochs are considered as compared to the space tug case study, which illustrates the extensibility of previously demonstrated applications.

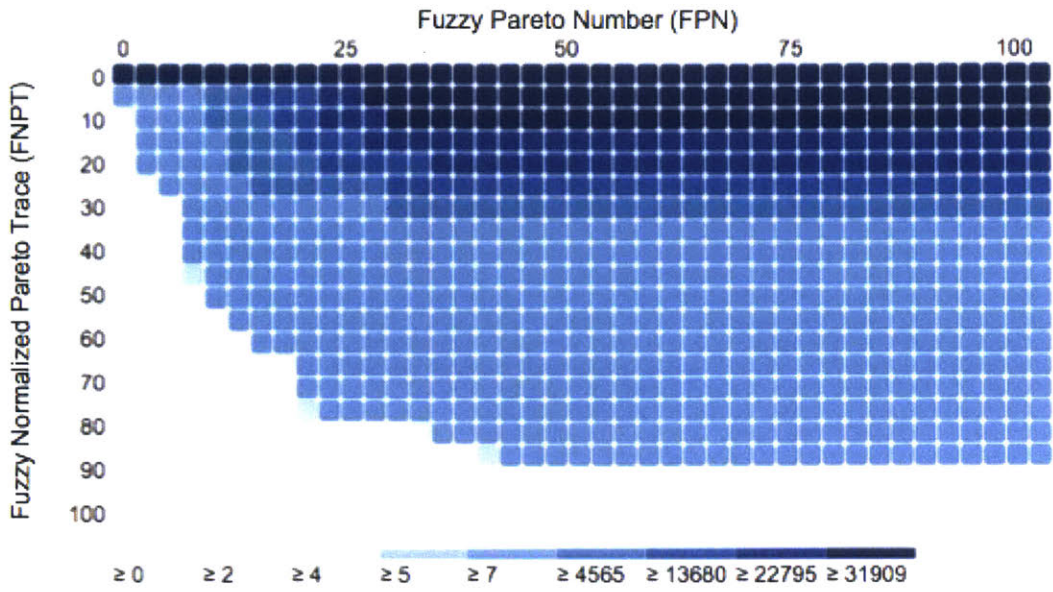
7.5.2.1 *Evaluating passive strategies for value sustainment (Robustness)*

In general, we want to have the lowest cost ship that can fulfill the technical requirements of a contract. Since ships that do not have the required technical equipment for an epoch are considered infeasible, the number of designs in the tradespace as well as its shape will change depending on the epochs. Equipment is typically a large cost driver, hence, trade-offs are likely required between optimality in any one epoch versus how many of the enumerated epochs can be satisfied when using passive strategies only. As with the previous case study, the percentage of enumerated epochs satisfied at a given fuzziness level is quantified using the fuzzy normalized Pareto trace (FNPT) metric. A proper exploration of the trade-off between “closeness” to the Pareto front (FPN) and passive robustness across various epochs (FNPT) is important when extracting insights from these large, high-dimensional data datasets that are produced in the design process.

When examining this trade-off, attempting to look at all data dimensions of all possible designs across all possible epochs can be daunting for decision-makers. Even with clever visual encoding, visualizations that show all the data could likely incur additional cognitive load for the users rather than reduce it. It can also be computationally burdensome and a barrier to scalability in case studies with large amounts of data points to consider, as was illustrated by the scatter plot in single epoch analysis. Furthermore, plotting every single data point, even if computationally feasible, can often not even be perceived by the analyst. Fortunately, depending on the task they are focused on, an internal mental representation of all data is not strictly necessary for an analyst. The interactive heatmap visualization shown in Figure 7-6 is one example of a simplified visualization that can show the compromise between Pareto efficiency (FPN) of designs within an epoch and the frequency with which they maintain that level of efficiency across multiple epochs (FNPT).

As illustrated in Figure 7-6 for the offshore case, there are no designs that are Pareto optimal in all enumerated epochs. Note that there are only white tiles, which represent zero satisfactory designs, if we look below the 85% FNPT point on the chart.

Accepting designs slightly away from the Pareto front or relaxing the constraint that all epochs must be satisfied allows additional design candidates to be identified. The figure shows that the fuzziness (e.g. threshold FPN value) needs to be relaxed to approximately 40% for any designs to be in the fuzzy Pareto set for an estimated maximum 85% of all epochs. This indicates that, in fact, no ship can satisfy all contracts and that the most multifunctional passively robust ship can satisfy a maximum of 85% of the potential contracts requirements. In general, this is shown on the heatmap by noting that more designs become acceptable at a given FNPT level as we move to the right, which represents an increasing allowable FPN value. At FNPT values greater than 35% it can be observed that relaxing FPN further does not increase the number of acceptable designs. This tends to indicate that the limits of what can be achieved through passive robustness alone have been reached and any further gains will require changeability to allow the designs to adapt to changing futures.



Of 41024 designs 4 are within 40.0% (fPN) of Pareto optimal in 85.0% (fNPT) of enumerated epochs.

DesignID	Cost [m\$]	Length [m]	Beam [m]	Depth [m]	Cruise [MT]	POB [pp]	Power [kW]	LW [MT]	Mooring [t/y]	Fuel [t/y]	ROV [t/y]	DP [t/y]	PipeLay [t/y]	DfC [-]	DeckArea [m ²]	Dwt [MT]	Speed [kn]
9739	284	180	30	8	800	250	15000	600	1	0	1	1	1	0	1260	9463.9	16.8
10195	308	180	30	8	800	250	15000	600	1	1	1	1	1	0	1260	9463.9	16.8
19995	285	180	30	8	800	250	15000	600	1	0	1	1	1	1	1260	9463.9	16.8
20451	309	180	30	8	800	250	15000	600	1	1	1	1	1	1	1260	9463.9	16.8

Figure 7-6: Interactive heatmap visualization (top), inspection table (bottom) for the ships in the selected tile

An analyst using this type of interactive visual interface can extract deeper insights about trade-offs by setting filters on various data dimensions to explore how those constraints impact other data dimensions or the list of available designs. For the commercial ship case study, this can be applied to gain a better understanding of the impact of fuzziness (FPN) and cost constraints. For instance, the designs that tend to be acceptable in most epochs, explored in the heatmap visualization in Figure 7-6, also tend to be among the most expensive in the tradespace. In fact, no matter how much the

fuzziness threshold is relaxed, there are no designs that satisfy more than 85% of the epochs for a cost lower than \$285 million. An analyst interested in achieving a lower target cost would need to examine in detail the cost savings that could be achieved by eliminating certain epochs (e.g. contracts, missions) which would result in a lower FNPT.

The interactive heatmap provides a high-level overview of trades between efficiency and robustness. But does not answer the questions: if an analyst wants to examine more complex trade-offs, for example, how restrictions on cost or other performance attributes impact the trade-off between FPN and FNPT, or, alternatively, if an analyst wants to identify whether certain epochs, stakeholders or context variables are more problematic than others for system value sustainment or they have a disproportionate effect on restricting the space of available alternatives. This type of information cannot be obtained from the heatmap visualization or aggregate measures like FNPT. More complex or nuanced questions like these require the examination of additional data dimensions that can be difficult to visualize and can also present added computational challenges.

This type of analysis is possible, however, with the aid of a more sophisticated visual interface like the example shown in Figure 7-7, where a combination of online analytical processing (OLAP) and binned aggregation for fast filtering and interaction with larger data sets are applied. This visualization can also be easily scaled to case studies involving millions of designs and large numbers of data dimensions. This is possible because, rather than plotting every data point, each dimension is binned into a histogram that allows filters to be placed on individual data dimensions to see how that impacts the other dimensions in coordinated views. A list of candidate designs that match the filters is then displayed in the list on the right.

Filtered Design Space (change cost <\$100M, change time <90 days)

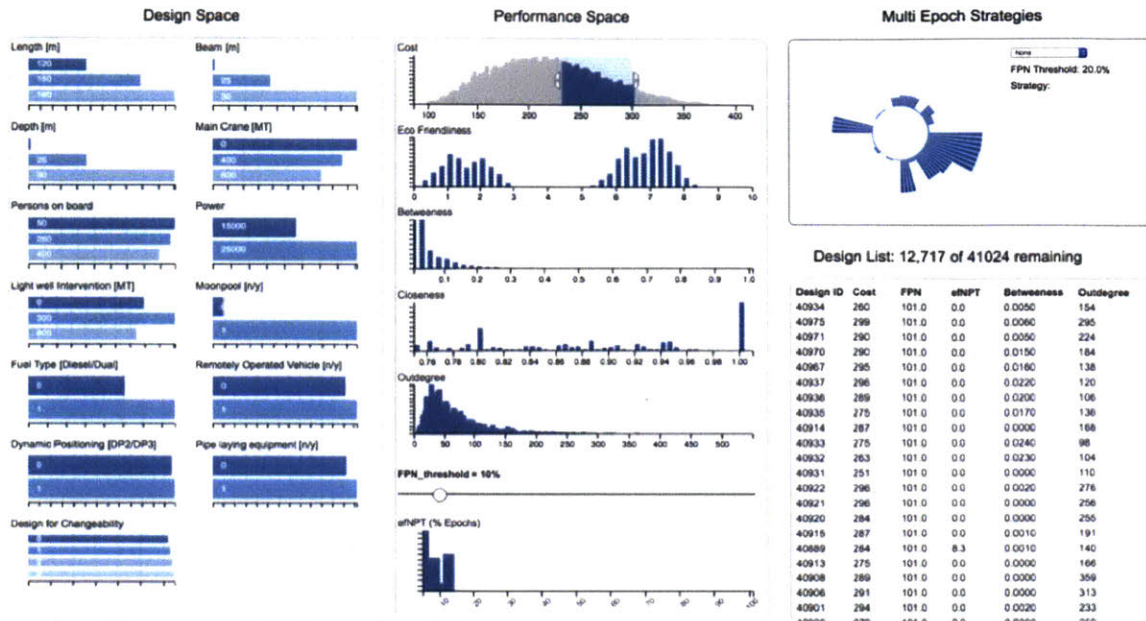


Figure 7-7: Interactive Filtering Application implementing OLAP for the offshore case (Filtered for allowable change cost < \$100M and change time < 90 days)

As was the case with the space tug case study, the Nightingale coxcomb diagram is also integrated into the OLAP driven visual interface for this case study in order to provide a comprehensive view of aggregate design performance in each enumerated epoch. For the ship case study the diagram shows all 96 epochs which is a factor of six greater than the number of epochs enumerated for the space tug case study. Figure 7-8 shows how the coxcomb diagram can be used to compare two different FPN thresholds (10% versus 20%) for designs that are passively robust. Note that chart zoom setting is such that the outer ring represents a yield of approximately 50% or, in other words, about 20,000 satisfactory designs in a given epoch. At an FPN threshold of 10% many of the epochs have relatively low yields which illustrates that these epochs are generally more difficult to satisfy. Several of the more easily satisfied epochs still only show yields from 5-20% at this FPN threshold. Increasing the FPN threshold to 20% results in similar efficiency scores for each epoch, but significant gains in yield. Still, the majority of the epochs (80 out of 96) still have yields lower than one-third even at this higher FPN threshold level. This is due in part to the fact that while many of the enumerated combinations of design variables represent feasible designs they do not have particularly good performance in many epochs.

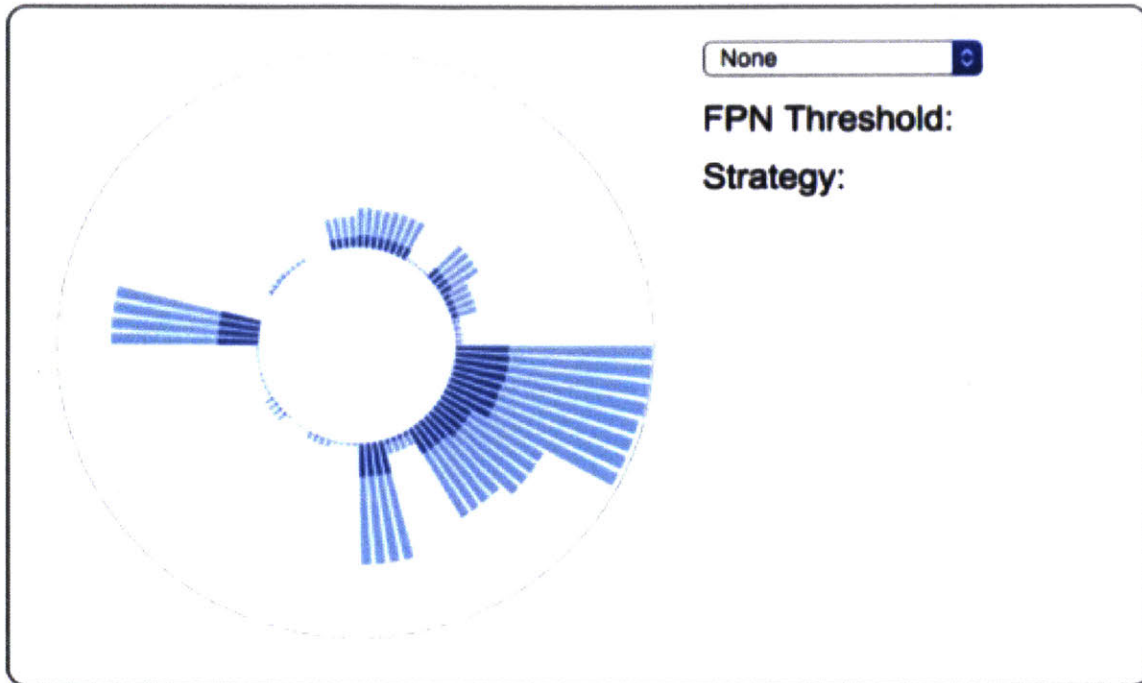


Figure 7-8: Nightingale coxcomb visualization for ship multi-epoch analysis comparing performance at an FPN threshold of 10% (dark blue) and 20% (light blue)

Filtering by epoch or epoch-level variables, though not demonstrated here, may provide further insights about why certain epochs are more difficult than others. This may also be useful for cases with larger numbers of epochs. While the Nightingale coxcomb makes a good compact visualization for a large number of epochs, displaying an infinite number of epochs would not be possible because of the pixel limitations of the screen. Focusing on a smaller number at any given time may not only be more comprehensible to the analyst, but also a necessity due to this limitation. Alternatively, filtering by epoch variables may also help identify what areas of the design may benefit most from adding changeability which will be discussed in the next section.

7.5.2.2 Evaluating active strategies for value sustainment (Changeability)

Implementation of changeability in the offshore ship case enables the system to mitigate risk and take advantage of opportunities in a future operational context. This is enabled by initially optimizing for the targeted contract, but also providing the flexibility to be able to change the design later based on the next state of operation, which is uncertain at the initial design stage. An offshore ship may be seen as a movable flexible platform that can carry equipment that enables the ship to take on contracts of various types. The equipment on deck can be retrofitted or swapped for equipment with different functionality if the ship has sufficient deck area. The ship must also possess sufficient stability characteristics that are largely driven by the shape of the hull (e.g. length, beam, depth). At an intermediate point in the ship design's lifecycle the size of the platform

may be changed, for example, through elongation ('jumboisation'), but at a higher cost, time and duration, compared to a traditional equipment retrofit on deck. Changing the hull generally requires the ship to be taken into port for some period during which time it is cut to be extended, contracted or otherwise reshaped.

Examining alternatives to the passive robustness approach demonstrated in the previous section the benefits of changeable designs can be visualized using the same visual application as before. For this study, the change options are the same as those described previously by Rehn et al. [164]. The change options in this case are operators on the design variables shown previously in Table 7-4. The change options are defined such that any design variable level can be changed to a different level assuming the resulting design is valid. In each case, both a change cost and time are defined. Figure 7-9 shows a comparison between a passive robustness strategy (dark blue) and a changeable strategy (light blue) at an FPN threshold of 10%. When using a changeability approach a maximize efficiency strategy is assumed similar to what was previously demonstrated for the space tug case study in Chapter 6. Looking at this broad overview first, it is clear that adding changeability generally improves the yield in each epoch and has only a small impact on average effective Pareto efficiency (eFPN). In fact, in most epochs, the yield is approximately doubled. Compare this to the result shown previously in Figure 7-8 that showed the impact of raising the FPN threshold and maintaining a passive robustness strategy. For that example, yields were approximately tripled when the FPN threshold requirement was relaxed. This example demonstrates how an analyst or decision maker may consider multiple approaches for finding more acceptable designs. If the FPN threshold cannot be lowered, or the decision maker simply prefers not to, a changeability strategy may be a more acceptable approach for them.

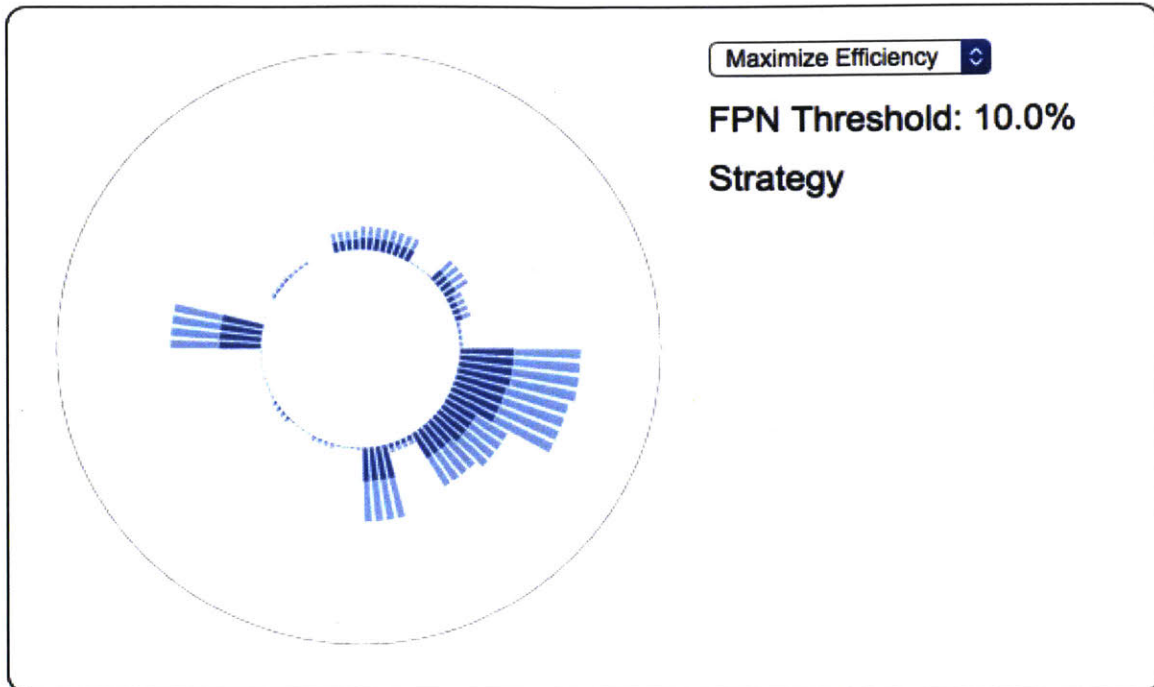


Figure 7-9: Nightingale coxcomb visualization for ship multi-epoch analysis comparing performance at an FPN threshold of 10% without changeability (dark blue) and with changeability using the maximize efficiency strategy (light blue)

But what if a designer wants to examine individual epochs that are either the best or worst performers to gain more insights? For example, consider epoch 25 that is generally a high-yield epoch for both changeable and passive robustness approaches. As with the space tug case study, an analyst can hover the mouse over any of the epoch wedges to get details on demand as shown in Figure 7-10. For this epoch, it shows that the baseline robustness strategy at an FPN threshold of 10% results in a yield for epoch 25 of approximately 13.3% and the yield increases to 29.3% when changeability is considered. Alternatively, if the FPN threshold is relaxed to 20%, the yield for epoch 25 increases to approximately 47.6%. A similar observation can be made for one of the more difficult epochs. Epoch 81, which is shown in Figure 7-11, has a yield of approximately 0.6% in the baseline passive robustness case and this increases to 1.3% and 1.6%, respectively, depending on whether we choose a changeable strategy or relax the FPN threshold as before.

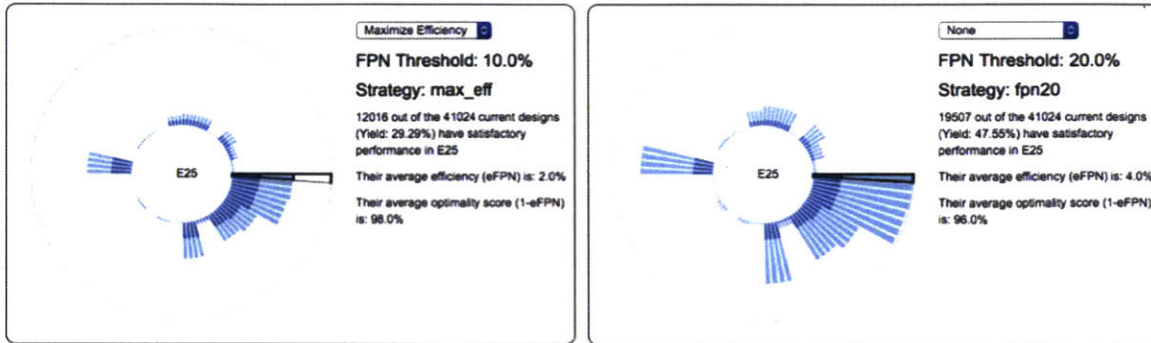


Figure 7-10: Comparing epoch 25 for a changeable maximize efficiency strategy (left) and a passive robustness approach (right)

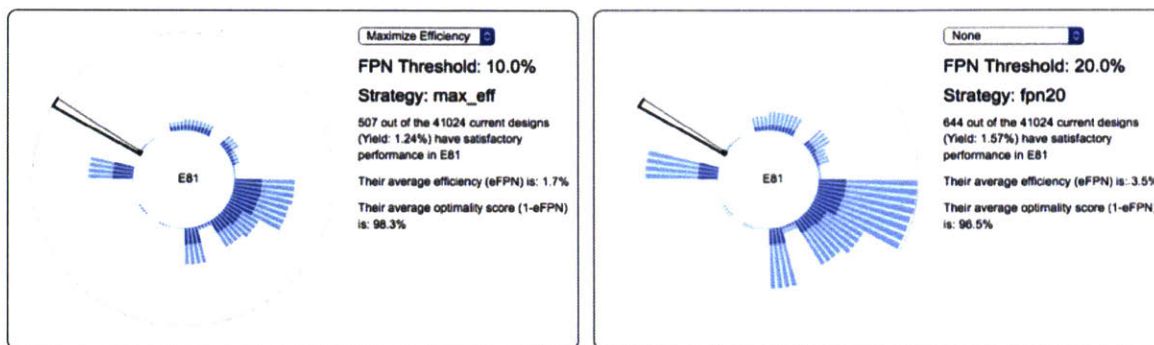


Figure 7-11: Comparing epoch 81 for a changeable maximize efficiency strategy (left) and a passive robustness approach (right)

Examining the designs that tend to perform well when we use a changeable approach with the maximize efficiency strategy reveals some other interesting insights. In general, the designs that perform well across most epochs tend to be ones with larger length, beam and depth that also tend to have large deck areas. This is likely the case because these designs can easily be retrofitted with different equipment to take on new missions. Designs that require modification to the hull must execute change options that are costly in terms of both time and money.

7.5.2.3 Summary of Multi-Epoch Analysis

The analyses outlined in this section provide a way for decision-makers to interactively evaluate the performance of multiple design alternatives across multiple futures. This creates opportunities for new insights at the expense of a potentially larger and more complex data set than what was considered for multi-epoch analysis which can be difficult to analyze. The application of an interactive framework and scalable interactive visualizations allows the analyst to engage with the data in new ways that can facilitate improved comprehension and decision-making. The insights that are extracted from this approach allow the decision-maker to understand the characteristics of designs

that can sustain value in all possible futures, through passive robustness or active changeability.

7.5.3 Process 8 and 9: Era Analyses

Epoch-analysis is focused on the evaluation of short run passive and active strategies for achieving value sustainment. In contrast, era-analysis focuses on long run sustainment of system value delivery across different missions or changing contexts. This process examines the time-dependent effects of several unfolding sequences of future epochs created in Process 4. Subject matter experts identified these epoch sequences as interesting narratives that might play out. By analyzing these particular sequences of epochs for a given length of time, analysts can identify potential strengths and weaknesses of a design and better understand the potential impact of path-dependent, long run strategies for value sustainment. The objective when analyzing these eras is for an analyst or decision-maker to identify the right combination of inherent robustness, changeability and operational strategy that allow a system to meet a specified performance threshold across all future time steps.

For the ship case study the problem was narrowed to six designs identified by subject matter experts that we would like to evaluate over the three narratively defined eras previously described. Further, two operational strategies described by Rehn et al. [164] were evaluated. These two strategies corresponded to a passive (e.g. no change) strategy and a maximize efficiency strategy. Note that more designs, eras and strategies could be analyzed here with acceptable increases in interactive latency. For instance, if we wanted to examine all the designs rather than just six of them, the histogram for design ID in interactive application shown in Figure 7-12 could be replaced with several histograms that represent the individual design variables to allow individual selection and filtering of all of them. This would not require that many additional visual elements rendered to the screen, but would require the definition of additional dimensions within the OLAP hypercubes. The interactive latency issues associated with the increased number of OLAP dimensions would likely be acceptable or at least easily overcome with additional processing power. However, recall Resnikoff's principle of selective omission described in Chapter 3, which describes how humans simplify and organize sensory information and abstract it to draw conclusions [86]. The conventional reasoning typically goes that even if you could render all possible data to the screen, a user couldn't perceive it or make effective use of it. Choices need to be made at each stage of analysis about how much information needs be analyzed, but this is not necessarily a limitation of IEEA.

Era analyses using interactive visualizations as shown in Figure 7-12 can aid in the assessment of different future lifecycles for the offshore design case. This visualization is an extension of the single-era analysis visualization demonstrated previously for the space tug case and contains four columns of coordinated views. The first column contains three row charts corresponding to designs, eras and strategies and enable filtering if an analyst only wants to view a subset of these at any given time. The second column contains time histories of several metrics of interest (MOI's) that allow

the user to adjust the window of time they are interested in focusing on. Each time history window contains one line for each design-strategy-era combination within the existing filters.

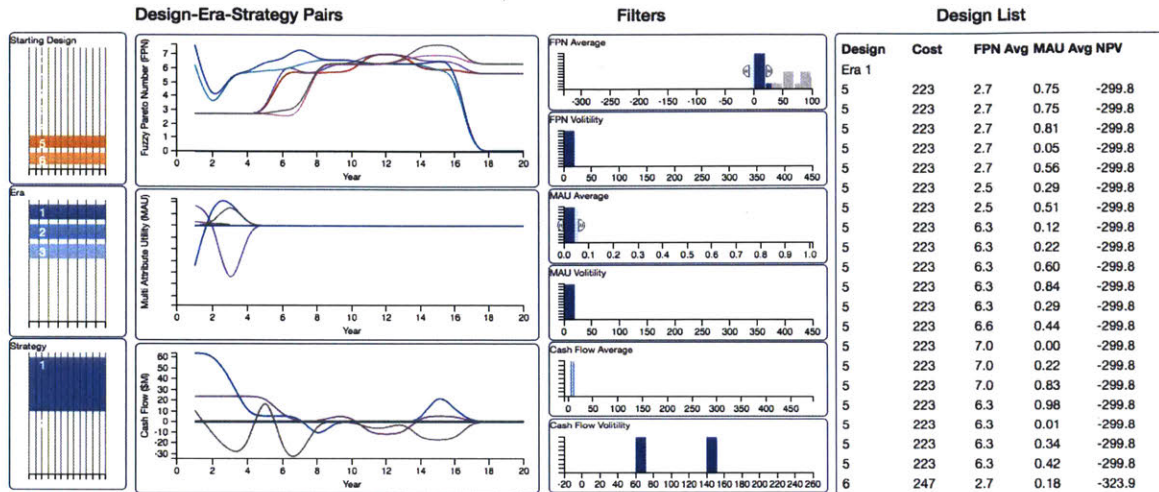


Figure 7-12: Interactive era analysis application implementing OLAP

Whereas the space tug case study focused on a single MOI, this case focuses on several time-varying MOIs beyond simply Pareto efficiency. For this case study, MOIs for both cash flows and multi-attribute utility are made available in addition to efficiency. Coordinated visualizations allow all three of these time-varying MOIs to be filtered by their time-weighted average and variability. The filterable histograms for the average and variability of each MOI are contained in the third column of the visualization. These additional metrics provide an improved ability to describe era performance at the expensive of increased information that a decision-maker must consider when selecting a design. Note that additional MOI's or more descriptive time history metric on the existing MOI's, as described in section 6.4.3, could have also been evaluated if we added additional views into the third column. However, based on expert-based evaluations of this application with ship SME's the current metrics were deemed sufficient. Finally, the fourth column provides the "details on demand" in the form of a scrollable list of designs and detailed information about the designs, strategies and eras remaining within the existing filter.

As demonstrated for previous IEEE processes, decision-making in era analysis can also benefit from the application of techniques such as multiple coordinated views, interactive filtering and OLAP. By limiting the number of visual elements that must be rendered on the screen and providing an efficient backend method for handling the data an analyst can efficiently filter the data to identify interesting design-strategy pairs. Implementing the interactive visualization in this way allows for future scalability to larger case studies as well if necessary.

7.6 Discussion and Conclusions

Application of IEEA to this case study for commercial offshore ship design demonstrates key concepts and interactive visualizations. This particular case study was selected to demonstrate the generalizability of IEEA to design problems in other domains. It also illustrates how the framework and interactive applications can be useful to SME's when applied to larger problems while overcoming issues related to scalability and latency. The primary hypothesis of this research is that leveraging research from the field of visual analytics to extend EEA can better address the design challenges that arise due to the quantity and complexity of data produced. In Chapter 3, four key areas of techniques from visual analytics were discussed: (1) heuristic and methodological guidance, (2) visualization, (3) data management and transformation, and (4) Interaction.

Regarding the first two areas, this case study demonstrates that they can, for the most part, be incorporated in the exact same way using the using interactive visualizations previously applied to the space tug case study. This strengthens the claim to generalizability, but it is worth pointing out a few of the challenges that were unique to this case study. First, for single epoch analysis, the large number of points that must be plotted in the interactive scatter plot can lead to issues with occlusion and increased interactive latency. To mitigate these issues, two-dimensional hexagonal binning was used to reduce the number of visual elements displayed and it was demonstrated that the perceptual scale can be modified by changing the bin size. This has the advantage of decreasing latency issues, but reduces functionality slightly because dot color and size can no longer be used to encode additional information. With further development, a modified version of this visualization may demonstrate functionality that allows the hexagonal bin size to be adjusted in real time by the user. Presumably, if they continued to make bin size smaller and smaller it would eventual be a representation of each point individually. Though more complex, this is a potential compromise that would improve scalability without limiting functionality. Another observation related to visualization scaling was that the wedges of the Nightingale coxcomb were significantly smaller in arc length as compared to the space tug example. Though they were still useful for comparing strategies in the example they may run into issues due to the pixel limitations of computer displays for case that had even larger numbers of epochs. This motivates a need for continued research and development into novel ways of displaying this information in follow-on research on IEEA.

The third area, data management and transformation, also showed some of the benefits and limitations of the techniques incorporated from visual analytics. While this case study showed that larger numbers of designs and epochs could be analyzed, no implementation will allow data to scale without eventual limits on storage and processing. Generation of the data for this study relied on parallel computing performed on a multi-core cluster that would not be available to all or even most users. Even when all the data can be generated, many of the data files associated with this case study were over 1GB in size which is approaching the limit of the amount of memory that can be allocated for these browser based tools regardless of the amount of local machine memory.

This closely relates to challenges observed with the fourth area through this case study, interaction. While the specific methods of interacting with the data were the same and OLAP techniques were extremely useful for manipulating and transforming the data, interactive latency could still quickly become a problem as data grows further. As with the space tug case, this case used tools that performed the OLAP data operations client-side. In other words, in the browser memory, which limits continued growth. Shifting many of the OLAP operations to backend server-side operations would be desirable as data sets continue to grow. Another option worth considering is GPU-based processing using WebGL as was demonstrated in research on the imMens technology demonstration [65]. In summary, this case study demonstrates the scalability, usefulness and generalizability of IEEA, but also illuminates some areas that are potentially ripe for future research. Additional research in these and other area may enable greater capabilities. These areas will be discussed in further detail in Chapter 8.

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8.0 Discussion and Conclusions

This thesis has described the IEEA framework and laid out the high-level processes and an integrated interactive visualization and analysis environment for its implementation that can be used to develop insights and comprehend factors that drive sustained value delivery from systems across changing conditions. As validation of the hypotheses of this research, the results of a controlled human subjects experiment and two case studies have been presented. They demonstrate how the coupling of EEA and research from the field of visual analytics can provide new capabilities to analysts and decision-makers.

This chapter provides the discussion and conclusions of this research. It begins by reviewing the three primary research questions and describing how this research responds to them and makes a unique contribution to the engineering literature. Some ancillary contributions outside the focus of the primary research questions will also be discussed. Lastly, several areas of potential future work that could follow on the research will be highlighted prior to providing the closing remarks of this thesis.

8.1 Summary of Research Questions

The following subsections summarize how each of the three research questions was addressed by the research described in this thesis.

8.1.1 Research Question 1

The first research question of this thesis research was:

(RQ1) How can the value sustainment of complex systems be enabled through an early-phase design framework that incorporates EEA and explicitly considers human interaction?

As a proof of concept, the IEEA framework and candidate interactive visualizations were introduced in Chapter 4 of this thesis to demonstrate how value sustainment is better enabled when human interaction is considered. Discretizing a system's lifecycle using EEA constructs provides a value-centric approach for analysts and decision-makers to model the impacts of changes in design, context or needs on perceived system value across uncertain futures. In past application of EEA, however, this has often resulted in large and complex data sets that create a barrier to value sustainment by making it difficult to analyze, understand and communicate the results. Examples of applications that implement the processes of IEEA have been introduced to demonstrate how value sustainment is better enabled through information-rich, interactive visualizations. For instance, the coordinated scatter plot and parallel coordinate visualization introduced for single epoch analysis demonstrates how the

design space can be explored efficiently without the loss of visibility into other data dimensions (e.g. design and performance variables) that occur when a tradespace is reduced to a simple cost versus utility scatter plot. Heatmap and coordinated bar graph visualizations demonstrate how binned aggregation techniques can be used to efficiently display the large amounts of information frequently encountered in multi-epoch analysis. IEEA provides a coherent theoretical framework to guide the development of these and other human-usable analytic tools.

It isn't just the information density of IEEA visualizations that better enables value sustainment, but also that they are interactive. The application of EEA constructs to design problems results in model-generated data sets that are often difficult to extract insights from due to their size, complexity, ambiguity or internal inconsistency. These differences motivate a shift from confirmatory data analysis, where visual representations are used to present results, to exploratory data analysis, which necessitates interaction with results by a human-in-the-loop (HIL). Interaction allows the HIL to zoom and filter to identify interesting subsets of the data, and choose the perceptual resolution at which they should be viewed to develop insights. This is especially important for large data sets where brute force automated analysis to identify patterns is not practical. The HIL is also needed in cases where there is ambiguity or lack of definition in terms of what is important in the data. In general, the framework and associated interactive visualizations provide several benefits that can aid in the design of systems with sustainable value as demonstrated through two case studies. The application of IEEA allows users to:

- Synthesize information from large amounts of data to better comprehend the nature of value delivery over time.
- Identify interesting patterns that result from important phenomenon
- Identify interesting patterns that are possibly due to model error.
- Gain higher confidence in decisions.
- Expand working memory.
- Communicate results and decision-making rationale.

Iterating among algorithmic data analysis and investigation using new visual representations and interactive capabilities, leads to continuous refinement and verification of results. This can lead to improved comprehension, higher confidence and allow consideration of a broader range of design options and operational strategies for value sustainment. The specific interactive visualizations for implementing IEEA processes shown in thesis are not intended to represent unique solutions. Rather, the IEEA framework and heuristic and methodological guidance from visual analytics serves as a guide for further development of interactive applications.

8.1.2 Research Question 2

The second research question of this thesis research was:

(RQ2) How can existing techniques from the field of visual analytics be incorporated into EEA to enable analysis and comprehension of driving factors of sustainable system value in dynamic operating environments?

This thesis describes how specific techniques, technologies and heuristic and methodological guidance from the field of visual analytics can be incorporated to demonstrate IEEA as an integrated visual analytics system. Visual analytics applications for implementing IEEA enable large amounts of data to be synthesized quickly to identify interesting patterns and generate insights in new ways. As demonstrated by two case studies, this allows key factors that influence value delivery over time to be assessed and communicated. Visual analytics systems have several key components that provide different benefits to EEA and incorporate various existing techniques. In general, visual analytics systems have three main parts: (1) data management/transformation, (2) visual representations, and (3) interaction methods. Techniques have been incorporated from each of these three areas to demonstrate how IEEA can be operationalized as practical and scalable visual analytics applications (interfaces).

Effective data management and transformation techniques become more critical as data volume and complexity increases. In this research OLAP and data reduction/aggregation techniques have been incorporated into EEA applications to allow large data sets to be rapidly manipulated and displayed. Several of the applications demonstrated for multi-epoch and era analysis show how these techniques can be applied in EEA studies that consider large numbers of designs and/or epochs.

To gain new insights, several novel visualizations have been demonstrated in this research such as parallel coordinates, chord diagrams and coxcomb diagrams. Many toolkit-specific abstractions used in prior EEA studies, such as those provided by Matlab or Excel, are limited to a palette of standard charts and annotations that restrict communication and decision-making. To take advantage of more sophisticated techniques that require specification of visualizations as a hierarchy of marks with visual properties (e.g. shape, color, value) and behaviors (e.g. events, animated transitions), web-based technologies more common to visual analytics research (e.g. D3) have been incorporated in this research. Applicability of interfaces with multiple coordinated views, another technique adopted from visual analytics research, are also demonstrated as a beneficial way of generating insights by examining different simultaneous representations of the data.

Interaction with multiple coordinated views can provide even greater benefits for exploratory analysis by effectively exposing relationships in the underlying data. For instance, the single epoch analysis tool demonstrated in this thesis was comprised of an interactive scatter plot and parallel coordinate diagram that were coordinated. Hovering the mouse pointer over any point in the scatter plot would interactively highlight how that

design mapped to additional data dimensions in the parallel coordinate chart. This is just one of the mechanisms used to enable exploration of the data without cluttering the interface.

8.1.3 Research Question 3

The third and final research question of this thesis research was:

(RQ3) Does interactive visualization improve design problem decision-making and, if so, what are the relative contributions of representation, interaction or other factors to user performance?

This thesis research answers this question in the affirmative. For design problem tasks interactive visualization does result in quantifiable improvements in human performance on design problem decision-making tasks as measured by task accuracy, completion time and cognitive load. An individual’s innate spatial reasoning ability also factors into their performance on these tasks.

Table 8-1: Overall impact of treatment group

Treatment	Graph?	Interactive capability?	Overall Accuracy	Average Completion Time (minutes)	Cognitive Load
A (control)	No	No	73.9%	14.3	0.483
B	Yes	No	85.5%	13.4	0.386
C	No	Yes	80.3%	8.1	0.345
D	Yes	Yes	90.6%	7.7	0.387

As described in detail in Chapter 5, a controlled experiment was designed and implemented to better understand how interactive visualization improves decision-making for design problems like those that are the focus of this thesis. By controlling variables associated with the type of interface provided, the experiment allowed the impacts of visualization and interaction on human performance to be decoupled and evaluated. Information on factors related to the subjects’ personality characteristics and spatial reason ability was also collected to evaluate any impacts on human performance. As shown in Table 8-1 the group given an interactive visualization (group D) performed better in all human performance categories measured by the experiment. Other key take-aways from this experiment include:

- **Task Accuracy**
 - The type of interface used to answer design task questions influence task accuracy. Specifically, adding a graph improves accuracy on trend observation tasks and adding an interactive capability improves accuracy on sorting tasks.

- Presence of a graph or interactive capability becomes more important as the number of data points associated with the task increases.
- Accuracy is strongly correlated to an individual's spatial reasoning ability when either a graph or interactive capability is present.
- **Completion time**
 - The effects of adding a graph are small, but adding an interactive capability significantly reduces the time required to solve design task problems. This effect is most prominent on tasks that have 25 or more data points associated with them.
 - There is no clear correlation between task completion time and individual personality characteristics.
- **Cognitive Load**
 - Adding a graph or interactive capability reduces cognitive load, but adding both does not further reduce the perceived load.
 - Reported drops in mental and temporal demand as well as lower levels of frustration are the primary drivers of reduced cognitive load.
 - Cognitive load has a strong negative correlation with spatial reasoning ability. As spatial reasoning ability increases, cognitive load decreases significantly. This correlation is even stronger when an interactive capability is available.

8.2 Research Contributions

The research described in this thesis makes several contributions to the engineering literature. The primary contributions as well as some ancillary ones are described in this section.

8.2.1 Summary of Primary Contributions

This thesis makes three primary contributions:

1. **Develops a generalizable prescriptive design framework that incorporates EEA with consideration for human interaction.**

Existing frameworks that incorporate EEA focus on how to organize a design problem into a series of activities, or sub-problems, that output qualitative or quantitative information. Though useful for general guidance, this does not provide a coherent theoretical framework to guide development of human-usable analytic tools. Increasing data volume and complexity encourage us to reexamine our approaches to balancing computer automation with human intuition in systems engineering decision-making. To that end, Chapter 4 introduces the IEEA framework, shown in Figure 8-1, to address these challenges.

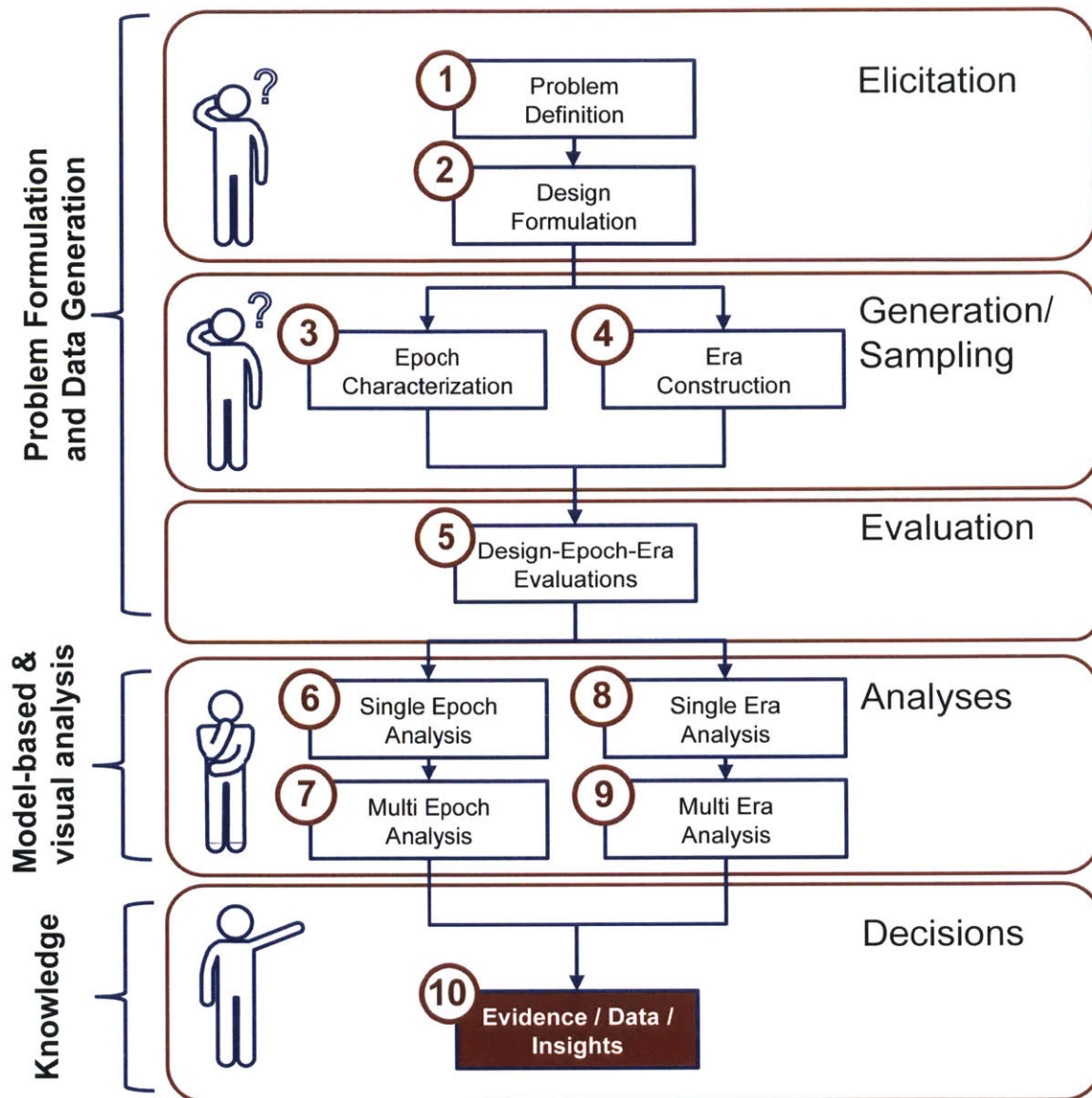


Figure 8-1: Interactive Epoch-Era Analysis process and modules.

IEEA extends upon prior frameworks in several ways. First, with inspiration drawn from the visual analytics process, the framework is expanded to include 10 processes grouped in 6 modules. This modularized approach provides consideration for implementation as well as multiple iterative and non-sequential workflows that are possible among the process steps. In addition, the new framework views the design process as a collaborative effort between human and computer. This therefore requires consideration of how inputs (interactions) should be provided and what outputs (visualizations) are necessary to enable effective communication. Specific visualization and interaction methods for IEEA process steps are shown in Chapter 4 and demonstrated through application to two case studies. These interactive visualizations draw on

guidance from visual analytics research discussed in Chapter 3, but are not necessarily intended to represent unique solutions or implementations of each process.

2. Demonstrate feasibility, usefulness and scalability of IEEA as an integrated visual analytics system.

Analysis applications developed in past studies have typically been structured to take some model-generated data as an input and transform it using a serialized algorithm to generate an output for the user. The interactive applications demonstrated in this thesis, a sampling of which are shown in Figure 8-2, are distinctly different in that they are designed to run continuously with frequent human interruption and redirection. This creates new types of challenges for practical implementations. This thesis introduces a scalable, database-driven web architecture for implementing IEEA that draws on technologies from visual analytics for data management and transformation, and interactive visualization.

This novel architecture provides a number of benefits. First, it is designed to accommodate cases studies with data sets that are large both in terms of number of records and their dimensionality. These large, multivariate data sets can be rapidly manipulated using OLAP techniques to generate aggregations that facilitate interaction. Second, the use of techniques that allow more detailed specification of visual and behavior properties of graphical elements allows much more sophisticated, interactive visualizations. Finally, the open architecture provides opportunities for future improvements of interactive applications as IEEA research evolves.

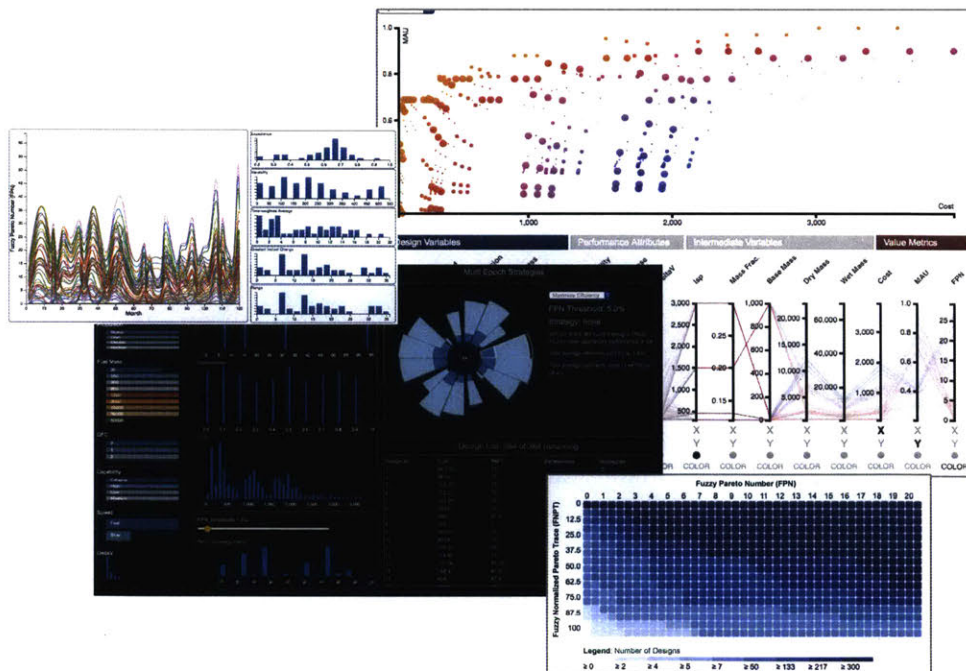


Figure 8-2: Sampling on interactive visualizations developed for this thesis research

3. Experimental characterization of the benefits of visual analytic applications for engineering design and impact of individual differences.

No prior research studies have quantified the relative contributions of the two main components of visual analytic systems (representation and interaction) while performing engineering design tasks. Chapter 5 describes a controlled human subjects experiment that was designed to decouple and evaluate the impact of these factors on human performance measured in terms of accuracy, speed and cognitive load (summarized in Figure 8-3). In addition, the experimental results provide visibility into how performance is impacted by factors such as task type, data volume and individual personality differences.

Because the surrogate design problem used in the experiment closely mirrors the challenges of an actual multi-epoch design problem, the results can offer some intuition about the types of elements that are important when constructing interactive applications for IEEA. Specifically, knowing how the objective of a given task maps to the type of element (e.g. graph, table) and the nature of the assistance the application should provide. Further, this experiment also shows that improvements in accuracy are strongly correlated to subjects' spatial reasoning abilities, but improvements in task speed are not. Knowing that an individual's innate characteristics are relevant to their performance opens up possibilities for pre-screening users or, alternatively, providing targeted assistance by allowing interactive applications to adapt to their user. The results of this experiment demonstrate the potential benefits that IEEA applications can provide and may also improve future interactive applications intended for engineering system designers.

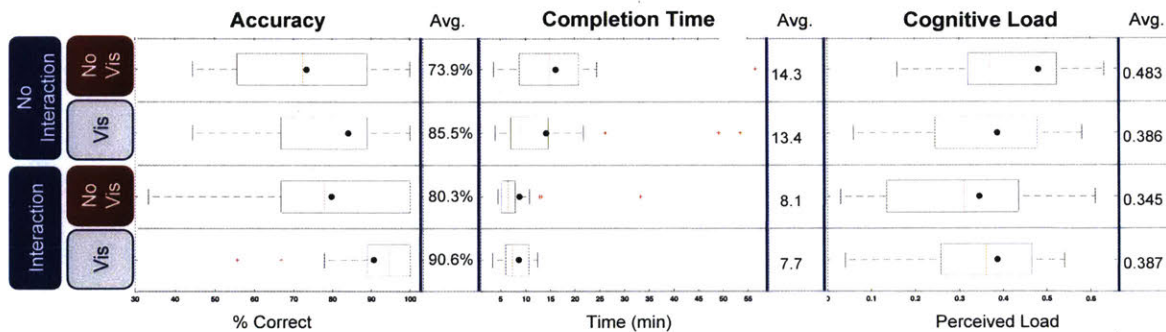


Figure 8-3: Summary of experiment results by treatment group

8.2.2 Additional Contributions / Observations

In addition to the primary contributions of this thesis there are also some ancillary contributions that result from this research. Some examples include:

1. The use of centrality metrics for multi-epoch changeability analysis

Past applications of EEA have used multi-epoch analysis to study changeability. Typically, these studies have used outdegree, or a filtered or utility-weighted version of it, as a metric for assessing the valuable changeability of designs. For the case studies discussed in this thesis the use of other centrality metrics, such as closeness and betweenness centrality, were examined to see if they provided additional benefits. The results suggest that betweenness centrality, when used to evaluate the tradespace network represented by the full-accessible matrix, may be useful in identifying designs exhibit interesting change behavior in subsequent era-analysis. Further research in this area, with a focus on how network analysis techniques in general can provide benefits, is recommended.

2. Enable distributed/collaborative design application

Although not a focus of this thesis research, an interesting byproduct of the use of web technologies is that they enable multiple distributed users to simultaneously use the same application. This has several ramifications. First, it means that users can access and use these design applications not only from computers anywhere in the world, but also mobile platforms like phones or tablets. Because most of the processing occurs on the server side the devices using the application don't have to be very powerful. With some minor modifications to the existing architecture it would also be possible to engage in collaborative design. This would effectively be a "Google docs" type of application where multiple system designers could engage with a particular design study simultaneously to solve problems. Coupling this with recent research in multi-stakeholder decision making in tradespace exploration [169] would enable some potentially interesting applications.

8.3 Limitations and Applicability

As with any research, limitations and assumptions exist within this thesis research. There are four main areas that this research does not address in detail that lead to limitations, but also create opportunities for future work that will be discussed in the next section. At a high-level, the areas are:

- EEA constructs and modeling considerations
- Interactive visualization development and applicability
- Collaborative capabilities
- Performance of interactive applications

8.3.1 EEA constructs and modeling considerations

IEEA incorporates constructs, methods and metrics from prior EEA research which impacts the generalizability of the research described here. IEEA was developed to be broadly applicable to early-stage conceptual design problems with uncertainty in future needs, context or system changes over time, but does come with assumptions that imply, among other things, that as EEA constructs and metrics mature in the future IEEA should be adapted as well. Chief among the assumptions embedded here are that the system and how the stakeholder(s) derive value from it can be modeled sufficiently enough to be able to base a decision on the model output. This doesn't mean that the models necessarily have to be the highest fidelity, just that they are good enough so that the behaviors decision-makers may need to identify can be distinguished from noise. In fact, in some cases, trying to model the system to a fidelity that is higher than necessary can increase the computational burden to a point that the models cannot be evaluated frequently enough to generate sufficient data upon which to base a decision. It also doesn't mean that models should be, at least initially, error-free. The IEEA process is in fact designed to encourage system modelers to question the embedded assumptions of their models and improve them as they iterate through process steps.

This thesis has touched on the challenges that come up throughout the conceptual design process, but has focused most of the attention on the analysis processes of IEEA. This is not intended to understate the importance of incorporating interactive visualization applications that can be beneficial to the elicitation, generation, sampling and evaluations modules of IEEA. Because many of the systems that future users of IEEA are developing are, by definition conceptual, and frequently a first-of-their-kind type of system, their performance and value proposition are not necessarily based on a lot of data collected from the real world, but are rather speculative. This implies that both the system model(s) and value model(s) cannot be completely validated in the traditional sense. The elicitation module could be difficult to develop because, unlike the analysis module, the process is not based on the evaluation of particular metrics. The tools that implement it are useful only if they can help a user update their mental model and better understand the problem so they can better characterize it, thus tool development may require some trial and error or more research in cognitive psychology. The generation and sampling modules could also be challenging to develop. Most case studies previously performed to demonstrate EEA have been based on full-factorial enumerations of the design and epoch spaces. This is clearly not feasible for studies that want to consider large number of variables and levels. To overcome this problem an interface developed for generation and sampling could allow selection (for instance through a dropdown menu) of alternate experimental designs, such as a central composite, latin hypercube or an adaptive sampling design. Such an interface may also allow a user to perform an a priori variable screening analysis, such as a Cotter screening design, to cull out variables that only weakly impact the analysis. Challenges arise, however, because it will difficult to quantify the degree to which the space of designs and epochs has been covered and whether it has been done so efficiently or not.

8.3.2 Interactive visualization development and applicability

This thesis has touted the benefits of applying the IEEE framework to guide the development of interactive tools for system design. However, the development of customized interactive tools does come with drawbacks. Compared to the use of off-the-shelf plotting functions for more standard visualization types, like those available in Excel or Matlab, many of the customized visualizations described in this thesis require more time to develop. The creation of sophisticated, customized D3-based visualizations requires lower-level detailed specification of the visual and behavioral properties of the elements on the screen. Essentially this trades increased development time for the ability to create more expressive and interactive visual interfaces.

In some cases issues related to learnability of some of the more sophisticated interfaces may also exist. Anecdotally, during the expert-based reviews of prototype tools in this research, it was observed that some of the subject matter experts would initially confuse the parallel coordinate chart, used for single-epoch analysis, as a line chart intended to display a time history. Parallel coordinate charts are not always familiar to users and therefore it sometimes takes some experience with them to appreciate their benefits and observe patterns within them. Similarly, some of the other more unique interfaces like chord diagrams or the coxcomb diagram, used in multi-epoch and multi-era analysis, take time to become proficient with. Much like the gauges on an airplane have obvious interpretations to a trained pilot, but can be cryptic to a layman, level of prior knowledge matters. This is related to another possible issue of which future researchers and developers of interactive tools should be aware. Differing levels of prior knowledge influence how individuals may learn or interpret new techniques. This is often referred to as the Kalyuga expertise reversal effect [170] that implies that individuals that are experts at prior methods of analysis may initially have difficulties learning how to interpret an interface and identify insights.

8.3.3 Collaborative capabilities

Another potential limitation of the current research is related to the assumptions that are embedded in the current interactive visualization prototypes. Specifically, each of the interfaces is designed for a single user following a “1-click, 1-response” paradigm. Similar to how Google Docs allows collaborative document editing, the web-based implementation of current tools theoretically enables multiple distributed users to be connected and working within a common workspace simultaneously. However, the discussion within this thesis has been scoped to focus on how a single user interacts with an interface. It is further assumed that when working with these interfaces each user interaction (such as dragging a brush filter) will result in only a single response (an update to the visualization). Opportunities to make tools even more collaborative with users exist if, for instance, tools were modified to attempt to interpret user interactions and predict their needs so that the interface could be adapted (visualization updated). Alternatively, the interactive tool could provide suggested actions to the user, similar to how older versions of Microsoft Office had the Clippy virtual assistant [171].

8.3.4 Performance of interactive applications

As decision-support tools become more capable they will likely push analysts and decision-makers to evaluate more design alternatives and future scenarios, so that they are more confident in their solution, or evaluate the same amount of information more quickly, so that they can reduce development time. For this reason, no matter how much data they can handle or how quickly they allow a user to interact with it, interactive tools will always tend towards limitations in available computing power and data storage. This motivates the need to continue to explore faster and more efficient “backend” techniques like GPU and parallel computing. It also suggests that future research could be useful on how to cast the problem definition in a way that encourages decision-makers to more effectively recognize when they’ve analyzed enough so that they don’t get locked in “analysis paralysis”. These areas and other suggestions for future work that may overcome some of the limitations of this research are discussed in more detail in the following section.

8.4 Future Work

The opportunities for future research are practically limitless, but several important areas suggested by this research are briefly described in this section.

1. Additional development of interactive visualizations

The interactive visualizations shown in this thesis were developed with continuous feedback using informal review from subject matter experts. Refinement of the existing visualizations and development of new ones is expected to continue for each of the processes of IEEA. Additional expert review and more extensive user testing on real-world applications is likely to generate new ideas for customized visualization types and interaction methods. Parts of this future effort will likely drive improvements in existing visualizations such as more scalable versions of parallel coordinate diagrams and force directed graphs. Research may also focus on the development and use of new interface types such as touch interfaces and distributed mobile platforms.

2. Interactive visualization for epoch and era characterization and construction

Interactive applications that effectively implement the epoch and era characterization and construction processes of IEEA could result in computational efficiencies and improved analytical capabilities. Epoch spaces for most EEA case studies are created by using a full or fractional factorial experimental design to enumerate combinations of the epoch variables. An interactive application that allowed a human-in-the-loop to enumerate the space in other ways could intelligently limit the size of the epoch space. For instance, allowing selection of other experimental designs, such as central composites, latin hypercubes or adaptive sampling techniques, could allow a human user to limit the epochs under consideration to a quantity appropriate to the availability of computational resources. Screening designs and real-time analysis of

parameter sensitivity could also allow a human user to identify epoch variables that are not significant drivers of main effects so that they can be culled from the analysis.

Interactive applications for era characterization and construction by a human user could also be valuable. An application for narrative era construction and some considerations for its implementation were previously discussed as an area of potentially useful future work by Schaffner [29]. To improve computational construction of eras, visual analytic tools that couple search algorithms with a human user could also allow more intelligent search of a wider range of the era space. Similar interactive tools for scenario planning, such as the interactive traveling salesman application demonstrated by Krolak [172], have shown promise in past research. Search algorithms, such as A-star or Primm's algorithm could be used for partial searches of the era tree guided by a human user to identify relevant path dependencies. Similar interactive applications could be useful, not only for era construction, but perhaps also for multi-era analysis.

3. Interactive applications that adapt to individual differences.

This research has demonstrated that individual differences between people impact the way, and degree to which, a user derives benefits from interactive applications. This suggests that it may be useful to develop future interactive applications that estimate a user's personality characteristics and adapt the interactive visualization to provide them the greatest benefit. Such applications could estimate key personality characteristics through a brief questionnaire as was demonstrated in this research or by tracking user behavior and forming estimates using machine learning algorithms as has been demonstrated by other researchers [144]. Using these estimates, a visual interface could be adjusted in various ways to adapt to the user. For instance, the visual layout could be adjusted to have a layout that is either more hierarchal or flatter depending on the user's locus of control which has been previously demonstrated as relevant to problem solving ability [143]. Colors, interaction method, or even how a visualization is labeled or annotated could be modified in real-time to better guide the user through the analysis.

4. Additional development on backend/computing related topics

Additional development of data generation and manipulation techniques could lead to more sophisticated visual analytic applications that can be applied to more complex case studies. Parallel computing using expandable cloud computing (e.g. Amazon EC2) for generating data sets was discussed in this thesis, but more seamless integration of this technique could be useful for reducing interaction latency when working with large data sets as well. Using GPU computing is another promising area of potential development. Prior work by other researchers have suggested such techniques can be used to feasibly implement applications with multiple coordinated views that are visually and interactively scalable [106]. A visual analytic system that uses WebGL to manipulate data using GPUs could allow interactive visualization of billions of data points in IEEA case studies.

5. Additional research on communication methods, evaluation of interactive visualization effectiveness and knowledge capture

This thesis has primarily focused on interactive visualization and how it can be used to analyze complex problems. Just as important is how it can be used to communicate findings and how that knowledge is captured for future use. Members of an engineering team can use interactive applications is to walk one another through their thinking directly. Alternatively, embedding interactive content within a web-based report could be another method of communication that would allow information to be distributed. In both cases, how interactive visualization is used to communicate results, and how to evaluate the effectiveness of that communication remains an open question.

A related area of future research is identifying ways to capture the knowledge that arises from the analysis so that it can be used in future studies. On many engineering projects the rationale for decisions made or the conclusions reached are held only in the heads of those individuals that worked on project. Capturing the decisions made and the chain of evidence used to reach those decisions is one aspect of creating institutional memory through visual analytic systems. Logging additional information such as model versions used, assumptions made and how much of the space of alternatives was explored before making a decision are other examples of knowledge capture. This information may prove useful to future studies by allowing the analysis of the rationale for past decisions or providing information about how to improve design tools.

6. Additional research on how humans process visual information in design problem analysis and decision-making

While this thesis has shown the visualization and interaction does impact human performance when working on design problems, it has not sought to rigorously examine the specific cognitive reasons these differences in performance exists. To trace the neural cognitive patterns of decision-makers when analyzing these types of problems one possible research extension could incorporate the use of functional magnetic resonance imaging (fMRI) to study the activity in the visual cortex. It has been suggested that, through collaboration with neuroscientists, the specific parts of the brain that activate when using various types of analytic tools could provide further insights as to why some of them enable improvements in performance.

8.5 Final Thoughts

As discussed at the beginning of this thesis, the goals of this research were initially driven by the needs of DoD's ERS research community. They expressed a desire for a comprehensive approach for early-stage conceptual design of systems that provide value to stakeholders across uncertain and changing futures. Problems like these are certainly not unique to the DoD or the ERS program, and often come up for many types of complex systems that have long lifecycles, long development times or are otherwise susceptible to uncertainty about the future. However, much of the early research among those interested in solutions for this class of problems has focused on the development of

tradespace exploration tools that assume a static context and set of stakeholder needs. User applications for tradespace exploration are often more simplistic in terms of data requirements and interpretation of their outputs, but they do not directly address questions about uncertain futures. EEA is more useful given their stated objective.

This research has explored the potential benefit of leveraging techniques from visual analytics to demonstrate how an integrated visualization and analysis environment, for making sense of high-dimensional EEA data, can lead to new capabilities and improved insights. Feedback on IEEA, and the initial implementations of the processes in interactive applications, has been positive from those within the research community as well as industry practice. Given the frequency with which questions come up regarding the availability of a commercial version of IEEA, it seems clear that the results of this research are beginning to address an unfilled need. It also seems likely that work on this research will continue over the coming years. This research hopefully provides a good starting point for further work in academia and practice.

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9.0 Appendices

9.1 Questions from spatial reasoning test

Section 1 of 3: Paper Folding Test


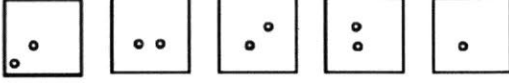

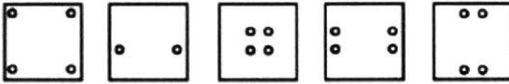

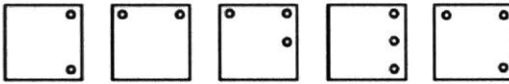

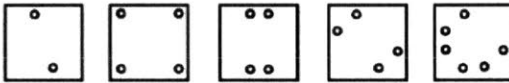

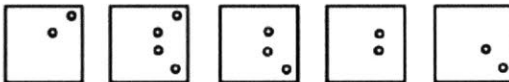

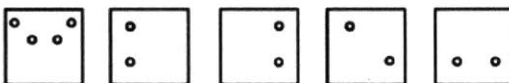

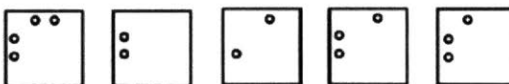

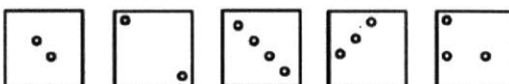

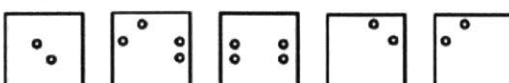

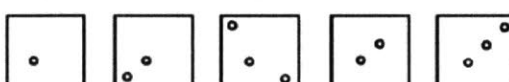
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Figure 9-1: Spatial reasoning test part 1

Section 1 of 3: Paper Folding Test continued

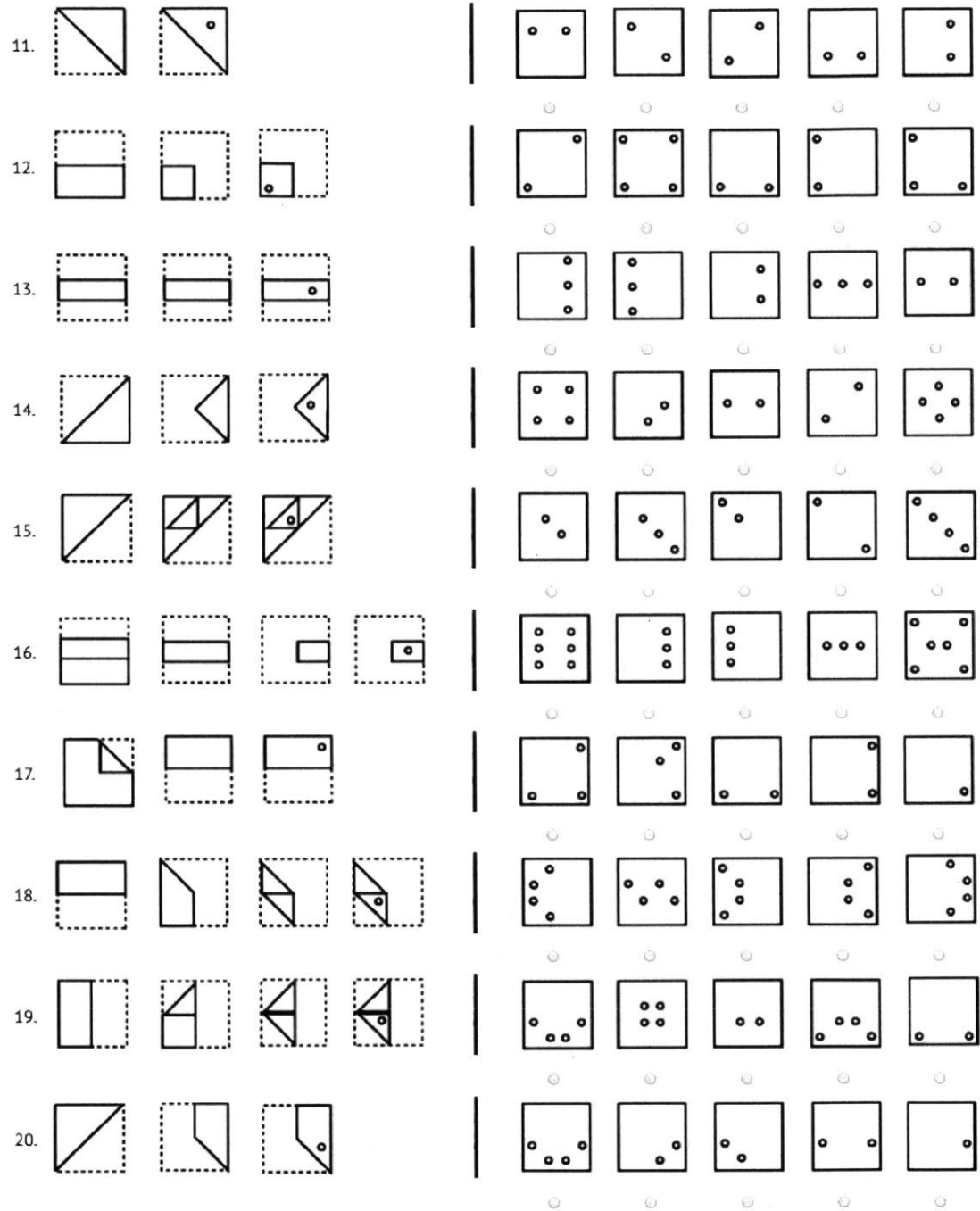


Figure 9-2: Spatial reasoning test part 2

9.2 Questions from personality inventory test

Section 2 of 3: Personality Inventory

Use the rating scale below to describe how accurately each statement describes *you*. Describe yourself as you generally are now, not as you wish to be in the future. This is not a test of your ability, and there are no right or wrong answers. Work quickly, giving your first reaction in each case, and make sure that you respond to every statement.

1. I believe that my success depends on ability rather than luck. Inaccurate 1 2 3 4 5 Accurate
2. I am the life of the party. Inaccurate 1 2 3 4 5 Accurate
3. I sympathize with others' feelings. Inaccurate 1 2 3 4 5 Accurate
4. I get chores done right away. Inaccurate 1 2 3 4 5 Accurate
5. I have frequent mood swings. Inaccurate 1 2 3 4 5 Accurate
6. I have a vivid imagination. Inaccurate 1 2 3 4 5 Accurate
7. I believe that unfortunate events occur because of bad luck. Inaccurate 1 2 3 4 5 Accurate
8. I don't talk a lot. Inaccurate 1 2 3 4 5 Accurate
9. I am not interested in other people's problems. Inaccurate 1 2 3 4 5 Accurate
10. I am paying attention. Select option three. Inaccurate 1 2 3 4 5 Accurate
11. I often forget to put things back in their proper place.. Inaccurate 1 2 3 4 5 Accurate
12. I am relaxed most of the time. Inaccurate 1 2 3 4 5 Accurate
13. I am not interested in abstract ideas. Inaccurate 1 2 3 4 5 Accurate
14. I believe that the world is controlled by a few powerful people. Inaccurate 1 2 3 4 5 Accurate
15. I talk to a lot of different people at parties. Inaccurate 1 2 3 4 5 Accurate
16. I feel others' emotions. Inaccurate 1 2 3 4 5 Accurate
17. I like order. Inaccurate 1 2 3 4 5 Accurate
18. I get upset easily. Inaccurate 1 2 3 4 5 Accurate
19. I have difficulty understanding abstract ideas. Inaccurate 1 2 3 4 5 Accurate
20. I believe some people are born lucky. Inaccurate 1 2 3 4 5 Accurate
21. I am paying attention. Select option three. Inaccurate 1 2 3 4 5 Accurate
22. I keep in the background. Inaccurate 1 2 3 4 5 Accurate
23. I am not really interested in others. Inaccurate 1 2 3 4 5 Accurate
24. I make a mess of things. Inaccurate 1 2 3 4 5 Accurate
25. I seldom feel blue. Inaccurate 1 2 3 4 5 Accurate
26. I do not have a good imagination. Inaccurate 1 2 3 4 5 Accurate
27. I believe in the power of fate. Inaccurate 1 2 3 4 5 Accurate

9.3 Questions from car design problem

Question 1 of 9: How many of the designs have a top speed greater than or equal to 89?

Answer : "3"

Type: "filter/aggregate"

Question 2 of 9: Of the designs that satisfy at least 2 customers segments when we allow 15% compromise, what is the cost of the third most expensive one?

Answer: "\$4650, design 7"

Type: "sort"

Question 3 of 9: We categorize designs into 4 groups by cost: low-end (\$3500-3999), mid-end (\$4000-4499), high-end (\$4500-4999) and ultra-high-end (\$5000-5500). For designs satisfying at least 1 customer segment at the 20% compromise level, which cost category has the most satisfactory designs?

Answer: "high-end: 3"

Type: "trend: 7 data points"

Question 4 of 9: How many of the designs have an mpg greater than or equal to 20?

Answer: "15"

Type: "filter/aggregate"

Question 5 of 9: Of the designs that satisfy at least 1 customer segments when we allow 10% compromise, what is the cost of the second most expensive one?

Answer: "\$4950, 17"

Type: "sort"

Question 6 of 9: We categorize designs into 4 groups by cost: low-end (\$3500-3999), mid-end (\$4000-4499), high-end (\$4500-4999) and ultra-high-end (\$5000-5500). For designs satisfying at least 1 customer segment at the 10% compromise level, which cost category has the least satisfactory designs?

Answer: "ultra-high-end, 1"

Type: "trend: 25 data points"

Question 7 of 9: How many of the designs have a reliability greater than or equal to 85?

Answer: "25"

Type: "filter/aggregate"

Question 8 of 9: Of the designs that satisfy at least 2 customers segments when we allow 10% compromise, what is the cost of the fourth most expensive one?

Answer: "\$5150, design 28"

Type: "sort"

Question 9 of 9: We categorize designs into 4 groups by cost: low-end (\$3500-3999), mid-end (\$4000-4499), high-end (\$4500-4999) and ultra-high-end (\$5000-5500). For

designs satisfying all 4 customer segment at the 20% compromise level, which cost category has the least satisfactory designs?

Answer: "high-end: 1"

Type: "trend: 100 data points"

9.4 Scalability methods for parallel coordinates

Though not yet implemented for IEEA visualizations like the single-epoch viewer, scalable methods for analyzing case studies with even larger numbers of designs then were demonstrated in this thesis may be useful. Two approaches in particular have been examined as candidate approaches for future implementations of IEEA: (1) Histogram coupling and; (2) Data scalable parallel coordinate plots (DSPCP).

The first method that can be considered is to couple histograms with the parallel coordinate plot, as shown in Figure 9-3, to offer an additional visual cue of the density of the lines at each axis intersection. In this example, each axis is augmented with a histogram of the data so that a user can more easily identify areas where large numbers of lines intersect. Brush filters could then be applied in a manner similar to the way they have been demonstrated elsewhere in this thesis. The benefit of this approach is that it is a relatively straightforward extension of the existing interactive application. It would simply require the rendering of a small number of rectangular elements to the existing parallel coordinate plot that would likely not be a substantial computational burden when rendering. The drawback of this approach is that it would still contain large numbers of overlapping lines that could potentially be a visual distraction to the user.

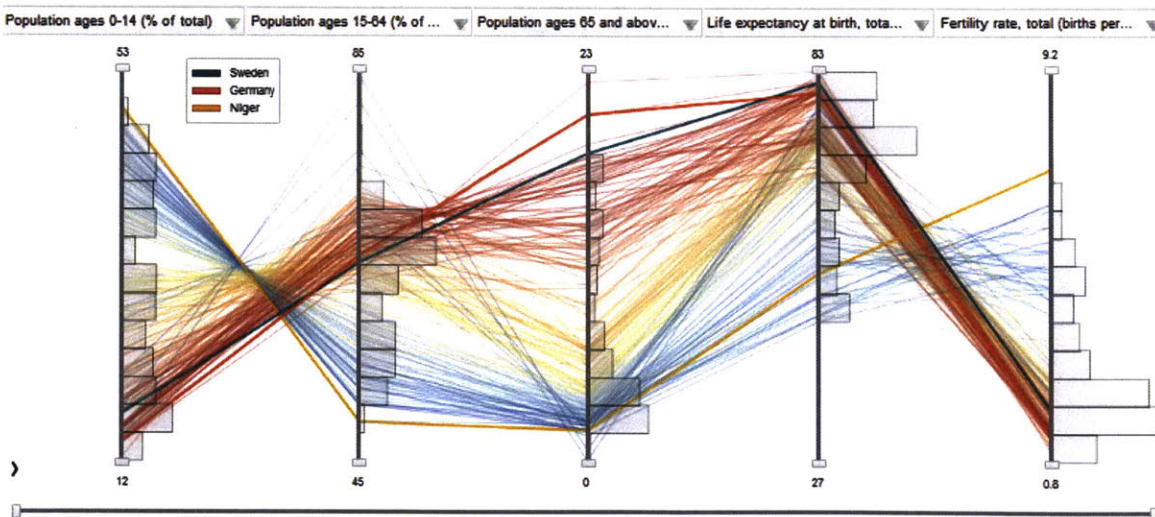
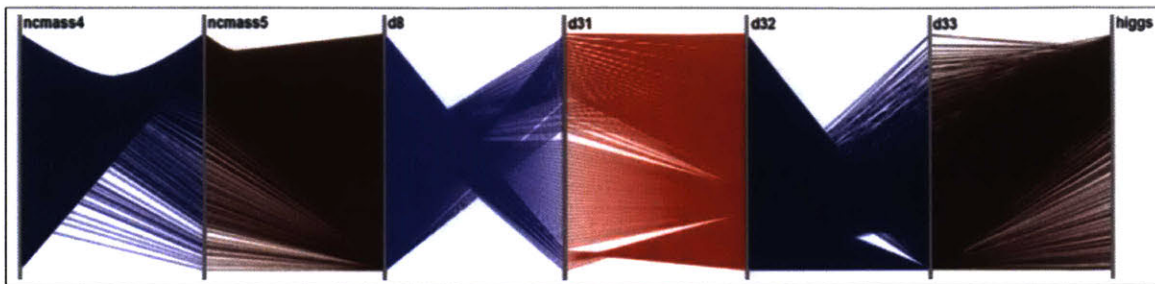


Figure 9-3: Parallel coordinates plot coupled with axis histograms [172]

A second approach that might be considered for plotting large numbers of data items with parallel coordinates is the data scalable parallel coordinates plot (DSPCP) proposed by Nguyen [173]. As shown in Figure 9-4, this approach resolves the overdraw problem with the lines by using K-means clustering and a unique approach for showing the density of overlapping lines. While this example may not seem intuitive at first, it is

possible that an analyst would learn to identify relevant patterns in the data as they gained more familiarity with the visualization.



(a) Conventional PCPs

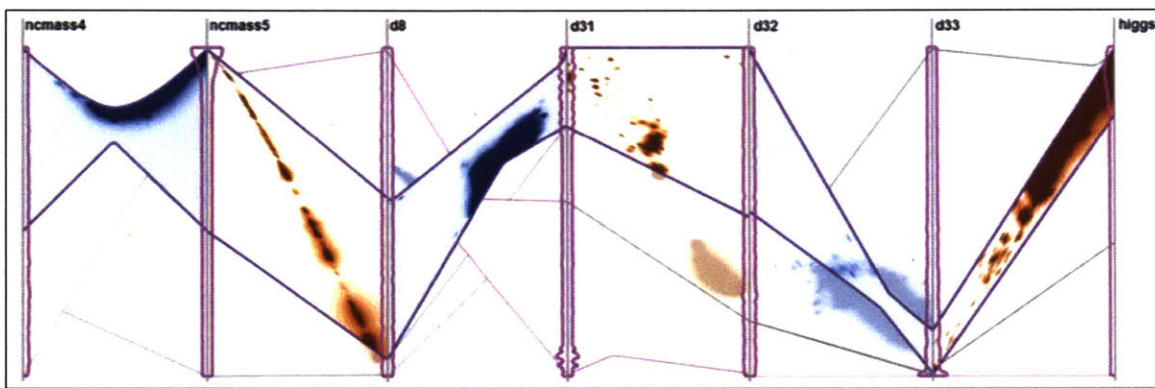


Figure 9-4: Data Scalable Parallel Coordinates Plot Example [173]

Note that neither of the approaches described here would necessarily resolve the problem of data dimensionality with parallel coordinate, just the number of data items. When large numbers of dimension also need to be displayed this can take up a lot of horizontal space on the screen and could compress the space between axes. This may make the identification of patterns challenging and interactions with the visualization difficult. One potential alternative if this issue arises is to consider a radar plot instead of a parallel coordinate plot. A radar plot can be thought of as a parallel coordinate plot wrapped around a circle rather than a horizontal line. This would potential provide more screen “real estate” for plotting all the dimensions by increasing the radius of the circle. This approach too, will eventually run into limitations due to screen size.

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10.0 References

- [1] Robert Neches, "Engineered Resilient Systems S&T Priority Description and Roadmap," in *NDIA 8th Annual Disruptive Technologies Conference*, Washington, D.C., 2011.
- [2] Jeffrey Holland, "Engineered Resilient Systems (ERS) A DoD Science and Technology Priority Area," in *Presentation, U.S. Army Engineer Research and Development Center (ERDC)*, 2013.
- [3] Simon Goerger, Azad Madni, and Owen Eslinger, "Engineered Resilient Systems: A DoD Perspective," in *13th Conference on Systems Engineering Research*, Redondo Beach, CA, 2014.
- [4] National Aeronautics and Space Administration (NASA), *NASA Systems Engineering Handbook*, 1st ed. Washington, DC, USA: NASA, 2007, NASA/SP-2007-6105 Rev1.
- [5] M. Bostock. (2014, May) Design is a Search Problem - Presentation to OpenVis Conference. [Online]. <https://www.youtube.com/watch?v=fThhb23SGM>
- [6] Clive Thompson, *Smarter Than You Think : How Technology Is Changing Our Minds For The Better*. New York, NY: The Penguin Press, 2013.
- [7] Loren G. Terveen, "An Overview of Human-Computer Collaboration," *Knowledge-Based Systems*, vol. 8, no. 2-3, pp. 67-81, April-June 1995.
- [8] David Gotz Jesus J Caban, "Visual analytics in healthcare – opportunities and research challenges," *Journal of the American Medical Informatics Association*, pp. 260-262, March 2015.
- [9] Remco Chang et al., "Wirevis: Visualization of categorical, time-varying data from financial transactions," in *IEEE VAST*, 2007.
- [10] Erin Miller, Kathleen Smarick, William Ribarsky, Remco Chang Xiaoyu Wang, "Investigative Visual Analysis of Global Terrorism," *Journal of Computer Graphics Forum*, vol. 27, no. 3, pp. 919–926, May 2008.
- [11] J. Thomas and K. Cook, "Illuminating the Path: The R&D Agenda for Visual Analytics National Visualization and Analytics Center," National Visualization and Analytics Center, 2005.
- [12] Robert Kosara, "Visualization Criticism – The Missing Link Between Information Visualization and Art," in *Proceedings of the 11th International Conference on Information Visualisation (IV)*, 2007, pp. 631–636.

- [13] Matthew Richards, "Multi-Attribute Tradespace Exploration for Survivability," Cambridge, MA, 2009.
- [14] Ben Corbin, "The Value Proposition of Distributed Satellite Systems for Space Science Missions," Cambridge, MA, September 2015.
- [15] Erik Hollnagel, David Woods, and Nancy Leveson, *Resilience Engineering*. Burlington, VT: Ashgate Publishing, 2006.
- [16] Matthew Richards, Daniel Hastings, Donna Rhodes, and Annalisa Weigel, "Defining Survivability for Engineering Systems," in *5th Conference on Systems Engineering Research*, Hoboken, NJ, 2007.
- [17] Scott Jackson, "A Multidisciplinary Framework for Resilience to Disasters and Disruptions," *Journal of Design and Process Science*, vol. 11, no. 2, pp. 91-108, 2007.
- [18] Scott Jackson and Azad Madni, "Towards a Conceptual Framework for Resilience Engineering," *IEEE Systems Journal*, vol. 3, no. 2, pp. 181-191, 2009.
- [19] Azad Madni, "Affordable, Adaptable and Effective: The Case for Engineered Resilient Systems," in *Engineering Resilient Systems Workshop*, Pasadena, CA, 2012.
- [20] J. Clark Beesmyer, "Empirically Characterizing Evolvability and Changeability in Engineering Systems," Cambridge, MA, 2012.
- [21] Eric Spero, Michael Avera, Pierre Valdez, and Simon Goerger, "Tradespace Exploration for the Engineering of Resilient Systems," in *13th Conference on Systems Engineering Research*, Redondo Beach, CA, 2014.
- [22] Wiley Larson and James Wertz, *Space Mission Analysis and Design (Third Edition)*. El Segundo, CA: Microcosm Press Kluwer Academic Publishing, 1999.
- [23] AIAA MDO Technical Committee, "Current state-of-the-art in multidisciplinary design optimization," 1991.
- [24] Ralph Keeney and Howard Raffia, *Decisions with multiple objectives: preferences and value trade-offs*. Cambridge, U.K.: Cambridge University Press, 1993.
- [25] Hugh McManus and Todd Schuman, "Understanding the Orbital Transfer Vehicle Trade Space," in *AIAA Space*, Long Beach, CA, 2003.
- [26] Adam, Hastings, Daniel, Diller, Nathan Ross, "Multi-Attribute Tradespace Exploration with Concurrent Design for Space System Conceptual Design," in *41st Aerospace Sciences Meeting*, Reno, NV, 2003.
- [27] Adam Ross, "Managing Unarticulated Value: Changeability in Multi-Attribute Tradespace Exploration," Cambridge, MA, 2006.
- [28] Adam Ross and Donna Rhodes, "Using Natural Value-centric Time Scales for Conceptualizing System Timelines through Epoch-Era Analysis," in *INCOSE International Symposium*, Utrecht, Netherlands,

2008.

- [29] Michael Schaffner, "Designing Systems for Many Possible Futures: The RSC-based Method for Affordable Concept Selection (RMACS), with Multi-Era Analysis," Cambridge, MA, 2014.
- [30] Matthew Fitzgerald, "Managing Uncertainty in Systems with a Valuation Approach for Strategic Changeability," Cambridge, MA, June 2012.
- [31] Matthew Fitzgerald, Adam Ross, and Donna Rhodes, "A Method Using Epoch-Era Analysis to Identify Valuable Changeability in System Design," in *9th Conference on Systems Engineering Research*, Los Angeles, CA, 2011.
- [32] Matthew Fitzgerald, Adam Ross, and Donna Rhodes, "Assessing Uncertain Benefits: a Valuation Approach for Strategic Changeability (VASC)," in *INCOSE International Symposium*, Rome, Italy, July 2012.
- [33] Lauren Viscito and Adam Ross, "Quantifying Flexibility in Tradespace Exploration: Value-Weighted Filtered Outdegree," in *AIAA Space*, Pasadena, CA, September 2009.
- [34] Lauren Viscito, Deb Chattopadhyay, and Adam Ross, "Combining Pareto Trace with Filtered Outdegree for Identifying Valuably Flexible Systems," in *7th Conference on Systems Engineering Research*, Loughborough University, UK, April 2009.
- [35] Daniel Hastings and Mary Cummings, "AFOSR Final Report "Architecting Science: Practical Tools for Architecting Flexible Systems"," Air Force Office of Scientific Research, Arlington, VA, August 2009.
- [36] Daniel Fulcoly, "A Normative Approach to Designing for Evolvability: Methods and Metrics for Considering Evolvability in Systems Engineering," Aeronautics and Astronautics, MIT, Cambridge, MA, Master of Science Thesis June, 2012.
- [37] Gergana Bounova, "Graph-theoretical Considerations in the Design of Complex Engineering Systems for Robustness and Scalability," Aeronautics and Astronautics, MIT, Cambridge, MA, SM Thesis.
- [38] Gergana Bounova and Olivier de Weck, "Graph-theoretical Considerations in Design of Large Telescope Arrays for Robustness and Scalability," in *1st AIAA Multidisciplinary Design Optimization Specialist Conference*, 2005.
- [39] Stephen Borgatti, "Centrality and network flow," *Social Networks*, vol. 27, no. 1, pp. 55-71, January 2005.
- [40] Stephen Borgatti and Martin Everett, "A Graph-theoretic perspective on centrality," *Social Networks*, vol. 28, no. 4, pp. 466-484, October 2006.
- [41] Linton Freeman, "A Set of Measures of Centrality Based on Betweenness," *Sociometry*, vol. 40, no. 1, pp. 35-41, March 1977.

- [42] Wikipedia. (2016, February) Centrality. [Online]. <https://en.wikipedia.org/wiki/Centrality>
- [43] Edsger Dijkstra, "A note on two problems in connexion with graphs," *Numerische Mathematik 1:* , vol. 1, pp. 269–271, 1959.
- [44] Vincent Blondel, Jean-Loup Guillaume, Renaud Lambiotte, and Etienne Lefebvre, "Fast unfolding of communities in large networks," *Journal of Statistical Mechanics: Theory and Experiment*, October 2008.
- [45] Adam Ross et al., "Responsive Systems Comparison Method: Case Study in Assessing Future Designs in the Presence of Change," in *AIAA Space*, San Diego, CA, September 2008.
- [46] Adam Ross, Hugh McManus, Donna Rhodes, Daniel Hastings, and Andrew Long, "Responsive Systems Comparison Method: Dynamic Insights into Designing a Satellite Radar System," in *AIAA Space*, Pasadena, CA, September 2009.
- [47] Remco Chang et al., "WireVis: Visualization of Categorical, Time-Varying Financial Transaction Data," in *IEEE Symposium on Visual Analytics Science and Technology (VAST)*, 2007, pp. 155–162.
- [48] Alvin Lee, Mohammad Ghoniem, Robert Kosara, William Ribarsky, Jing Yang, Evan Suma, Caroline Ziemkiewicz, Daniel Kern, Agus Sudjianto Remco Chang, "Scalable and interactive visual analysis of financial wire transactions for fraud detection Information Visualization," *Information Visualization*, vol. 7, no. 1, pp. 63-76, February 2008.
- [49] Ghoniem M, Kosara R, Ribarsky W, Yang J, Suma E, Ziemkiewicz C, Kern D, Sudjianto A. Chang R, "WireVis: Visualization of categorical, time-varying data from financial transactions," in *Proceedings Visual Analytical Science and Technology 2007 (VAST 2007)*, Sacramento, CA, 2007, pp. 155–162.
- [50] J. Caban and D. Gotz, "Visual analytics in healthcare--opportunities and research challenges," *Journal of the American Medical Association*, vol. 22, no. 2, pp. 260-262, March 2015.
- [51] Xiaoyu Wang, Wenwen Dou, Shen-En Chen, William Ribarsky, and Remco Chang, "An Interactive Visual Analytics System for Bridge Management," *Computer Graphics Forum*, vol. 29, no. 3, pp. 1033-1042, June 2010.
- [52] Xiaoyu Wang, Erin Miller, Kathleen Smarick, William Ribarsky, and Remco Chang, "Investigative Visual Analysis of Global Terrorism," *Computer Graphics Forum*, vol. 27, no. 3, pp. 919-926, May 2008.
- [53] P. Wong and J. Thomas, "Visual Analytics," *IEEE Computer Graphics and Applications*, vol. 24, no. 5, pp. 20-21, 2004.
- [54] J. Thomas and K. Cook, "Illuminating the Path: The R&D Agenda for Visual Analytics," 2005.
- [55] Daniel Keim, Jörn Kohlhammer, and Geoffrey Ellis, *Mastering the*

Information Age: Solving Problems with Visual Analytics. Goslar, Germany: Eurographics Association, 2010.

- [56] I. Icke and E Sklar, "Visual Analytics: A Multi-faceted Overview," April 16, 2009.
- [57] Daniel Keim et al., "Visual analytics: Definition, process, and challenges," in *Information Visualization*.: Springe, 2008, vol. 4950, pp. 154-175.
- [58] Guo-Dao Sun, Ying-Cai Wu, Rong-Hua Liang, and Shi-Xia Liu, "A Survey of Visual Analytics Techniques and Applications: State-of-the-Art Research and Future Challenges.," *Journal of Computer Science and Technology*, vol. 28, no. 5, pp. 852-867, September 2013.
- [59] Ben Shneiderman, "The eyes have it: A task by data type taxonomy for information visualizations," in *Proceedings of the IEEE Symposium on Visual Languages*, September 1996, pp. 336-343.
- [60] D Keim, F. Mansmann, J. Schneidewind, and H. Ziegler, "Challenges in visual data analysis," in *Proceedings of the IEEE Conference on Information Visualization*, October 2006, pp. 9-16.
- [61] Michael Bostock, Vadim Ogievetsky, and Jeffrey Heer, "D3: Data-Driven Documents," in *IEEE Transactions on Visualization & Computer Graphics (Proceedings of InfoVis)*, 2011.
- [62] Michael Bostock and Jeffrey Heer, "Protovis: A Graphical Toolkit for Visualization," in *IEEE Transactions on Visualization & Computer Graphics (Proceedings of InfoVis)*, 2009.
- [63] I. Fodor, "A survey of dimension reduction techniques," Livermore, CA, May, 9 2002.
- [64] Richard Holbrey, "Dimension reduction algorithms for data mining and visualization," , 2006.
- [65] Z. Liu, B. Jiang, and J. Heer, "imMens: Real-time Visual Querying of Big Data," in *Eurographics Conference on Visualization (EuroVis)*, Leipzig, Germany, 2013.
- [66] A. Inselberg, "Visualizing high dimensional datasets and multivariate relations (tutorial am-2)," in *Tutorial notes of the sixth ACM SIGKDD international conference on Knowledge discovery and data mining*, New York, NY, 2000.
- [67] D. Andrews, "Plots of high dimensional data," *Biometrics*, vol. 28, pp. 128-136, 1972.
- [68] Mihael Ankerst, Stefan Berchtold, and Daniel Keim, "Similarity clustering of dimensions for an enhanced visualization of multidimensional data," in *Proceedings of the International Conference on Information Visualization*, Triangle Park, NC, 1998.
- [69] A. Delorme and S. Makeig, "Eeglab: an open source toolbox for analysis of single-trial eeg dynamics including independent component

- analysis," *Journal of Neuroscience Methods*, vol. 134, pp. 9-21, 2004.
- [70] E. Chi, "A taxonomy of visualization techniques using the data state reference model," in *Proceedings of the IEEE Symposium on Information Visualization*, Washington, DC, 2000.
- [71] W. Cleveland and R. McGill, "The Many Faces of a Scatterplot," *Journal of the American Statistical Association*, vol. 79, no. 388, pp. 807-822, 1984.
- [72] D. Carr, W. Littlefield, and J., Littlefield, "Scatterplot Matrix Techniques for Large N," *Journal of the American Statistical Association*, vol. 82, no. 398, pp. 424-436, 1987.
- [73] A. Inselberg and B. Dimsdale, "Parallel coordinates: a tool for visualizing multi-dimensional geometry," in *Proceedings of the 1st conference on Visualization*, Los Alamitos, CA, 1990.
- [74] Daniel Keim, "Designing pixel-oriented visualization techniques: Theory and applications," *IEEE Transactions on Visualization and Computer Graphics*, vol. 6, no. 1, pp. 59-78, 2000.
- [75] J. Roberts, "State of the Art: Coordinated & Multiple Views in Exploratory Visualization," in *5th International Conference on Coordinated and Multiple Views in Exploratory Visualization*, Washington, DC, 2007.
- [76] M. Scherr, "Multiple and Coordinated Views in Information Visualization," in *Media Informatics Advanced Seminar on Information Visualization*, 2008/2009.
- [77] G. Andrienko and N., Andrienko, "Coordinated Multiple Views: a Critical View," in *5th International Conference on Coordinated and Multiple Views in Exploratory Visualization*, Washington, DC, 2007.
- [78] Jeffrey Heer and Ben Shneiderman, "Interactive Dynamics for Visual Analysis," *ACM Queue*, vol. 10, no. 2, p. 30, 2012.
- [79] Daniel Keim, "Information visualization and visual data mining," *IEEE Transactions on Visualization and Computer Graphics*, vol. 8, no. 1, pp. 1-8, 2002.
- [80] J. Heer and M. Agrawala, "Design considerations for collaborative visual analytics," *Information Visualization*, vol. 7, no. 1, pp. 49-62, 2007.
- [81] Xiaoqing Liu, Samir Raorane, and Ming Leu, "A web-based intelligent collaborative system for engineering design," in *Collaborative product design and manufacturing methodologies and applications*. London, UK: Springer, 2007, pp. 37-58.
- [82] M. O'Neal et al., "Framework for Assessing Cost and Technology: An Enterprise Strategy for Modeling and Simulation Based Analysis," in *MODSIM World 2011 Conference and Expo*, Virginia Beach, VA, October 14, 2011.
- [83] T. Ender, D. Browne, W. Yates, and M. O'Neal, "FACT: An M&S

- Framework for Systems Engineering," *The Interservice / Industry Training, Simulation & Education Conference (IITSEC)*, vol. 2012, no. 1, 2012.
- [84] D. Browne, R. Kempf, A. Hansen, M. O'Neal, and W. Yates, "Enabling Systems Modeling Language Authoring in a Collaborative Web-based Decision Support Tool," *Procedia Computer Science*, vol. 16, pp. 373-382, 2013.
- [85] V. Sitterle, M. Curry, T. Ender, and D. Freeman, "Integrated Toolset and Workflow for Tradespace Analytics in Systems," in *INCOSE International Symposium*, Las Vegas, NV, 2014.
- [86] Mackinlay, J., and Shneiderman, B. Card S.,.: Morgan Kaufmann Publishers, 1999, p. 686.
- [87] H.L. Resnikoff, *The Illusion of Reality*. New York, NY, USA: Springer-Verlag, 1987.
- [88] J. and Simon, H. Larkin, "Why a diagram is (Sometimes) Worth Ten Thousand Words," *Cognitive Science*, vol. 11, no. 1, pp. 65-99, 1987.
- [89] D.A. Norman, *Things that Make Us Smart*. Reading, MA, USA: Addison-Wesley, 1993.
- [90] Edward Tufte, *The Visual Display of Quantitative Information*. Cheshire, CT, USA: Graphic Press LLC, 1983.
- [91] S., Robertson, G., Mackinlay, J. Card, "The information visualizer; An information workspace.," in *ACM CHI*, 1991, pp. 181-188, New Orleans, LA (April 28 - May 2).
- [92] J. Bertin, *Graphics and Graphic Information Processing*. Berlin, Germany: De Gruyter, 1977/1981.
- [93] E. Hutchins, *Cognition in the Wild*. Cambridge, MA, USA: MIT Press, 1996.
- [94] Peter Krensky, "Interactive Data Visualization: The Age of "Look but don't touch" is over," *Analytics & Business Intelligence*, Aberdeen Group, Research 2014.
- [95] Robert B. Haber and D. A. McNabb, "Visualization idioms: A conceptual model for scientific visualization systems," in *Visualization in Scientific Computing*, B. Shriver, and L. J. Rosenblum Gregory M. Nielson, Ed.: IEEE Comp. Society Press, 1990, pp. 74-93.
- [96] E.H., Riedl, J. Chi, "An operator interaction framework for visualization systems," in *InfoVis: Proceedings of the 1998 IEEE Symposium on Information Visualization*, 1998, pp. 63-70.
- [97] S. and Brodlie, K. dos Santos, "Gaining understanding of multivariate and multidimensional data through visualization ," *Computers and Graphics*, vol. 23, no. 1, pp. 311-325, June 2004.
- [98] J., Card, S. and Landay, J. Heer, "Prefuse: a toolkit for interactive information visualization. ," in *SIGCHI conference on human factors in*

- computing systems*, 2005, pp. 421-430.
- [99] Y. K. and Apperley, M. D. Leung, "A review and taxonomy of distortion-oriented presentation techniques," *ACM Transactions Computer-Human Interaction*, vol. 1, no. 2, pp. 126-160, June 1994.
 - [100] (2017, January) Wikipedia: OLAP cube. [Online]. https://en.wikipedia.org/wiki/OLAP_cube
 - [101] W. Cleveland and R. McGill, "Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods," *Journal of the American Statistical Association*, vol. 79, no. 387, pp. 531-554, September 1985.
 - [102] J., Card, S., and Landay, J. Heer, "prefuse: a toolkit for interactive information visualization," in *ACM Human Factors in Computing Systems (CHI)*, Portland, OR, 2005, pp. 421-430.
 - [103] (2008, July) Flare: Data Visualization for the Web. [Online]. <http://flare.prefuse.org>
 - [104] dc.js - Dimensional Charting Javascript Library. [Online]. <https://dc-js.github.io/dc.js/>
 - [105] J. S., Kang, Y. A., Stasko, J., & Jacko, J. A. Yi, "Toward a Deeper Understanding of the Role of Interaction in Information Visualization. ," *IEEE Transactions on Visualization and Computer Graphics (TVCG)*, vol. 13, no. 6, pp. 1224-1231, October 2007, Presented in InfoVis 2007, October 28 - November 1.
 - [106] Zhicheng Liu. (2013, July) ISTC Big Data. [Online]. <http://istc-bigdata.org/index.php/immens-real-time-interactive-visual-exploration-of-big-data/>
 - [107] R.B. Miller, "Response time in man-computer conversational transactions," in *AFIPS Fall Joint Computer Conference*, vol. 33, 1968, pp. 267-277.
 - [108] Ofri Raviv. (2012, September) What is the threshold where actions are perceived as "instant"? [Online]. <http://cogsci.stackexchange.com/questions/1664/what-is-the-threshold-where-actions-are-perceived-as-instant>
 - [109] Jakob Nielsen, *Usability Engineering*, 1st ed. Cambridge, MA, USA: Academic Press, 1993.
 - [110] B. A. Myers, "The importance of percent-done progress indicators for computer-human interfaces," in *ACM CHI*, San Francisco, CA, 1985, pp. 11-17, 14-18 April.
 - [111] J. and Robertson, G. Heer, "Animated Transitions in Statistical Data Graphics," *IEEE Transactions on Visualization and Computer Graphics*, vol. 13, no. 6, pp. 1240-1247, November 2007.
 - [112] B., Cairns, P. Craft, "Beyond Guidelines: What Can We Learn from the Visual Information Seeking Mantra? ," *Proceedings of the Ninth International Conference on Information Visualisation*, pp. 110-118, July 2005.
 - [113] Edward Tufte, *Envisioning Information*. Cheshire, CT, 2001:

Graphic Press LLC, 2001.

- [114] William Playfair, *Commercial and Political Atlas*. London, UK, 1786.
- [115] C.J. Minard, *Carte Figurative des pertes successives en hommes de l'Armée Française dans la campagne de Russie 1812-1813*. Paris, France, 1869.
- [116] Florence Nightingale, *A contribution to the sanitary history of the British army during the late war with Russia*. London, UK: John W. Parker and Son, West Strand., 1859.
- [117] (2016, December) Wikipedia: Edward Tufte. [Online]. https://en.wikipedia.org/wiki/Edward_Tufte
- [118] Zach Gemignani. (2010, April) Better Know a Visualization: Small Multiples. [Online]. <http://www.juiceanalytics.com/writing/better-know-visualization-small-multiples>
- [119] (2017, January) Django Web Framework 1.10.5. [Online]. <https://www.djangoproject.com/>
- [120] (2017, January) Wikipedia: Model–view–controller. [Online]. <https://en.wikipedia.org/wiki/Model%E2%80%93view%E2%80%93controller>
- [121] M., La Tour, P., and Slagowski, S., Curry, "Multidisciplinary design optimization for a high-resolution earth-imaging constellation," in *IEEE Aerospace Conference*, Big Sky, MT, 2015.
- [122] J., Robertson, G., Heer, "Animated transitions in statistical data graphics," *IEEE Transactions Trans on Visualization Vis and Computer Comp Graphics*, vol. 13, no. 6, pp. 1240-1247, November 2007.
- [123] J. Nickel, "Using multi-attribute tradespace exploration for the architecting and design of transportation systems," MIT Engineering Systems Division, Cambridge, MA, SM Thesis 2010.
- [124] Chris Roberts, Matthew Richards, Adam Ross, Donna Rhodes, and Daniel Hastings, "Scenario Planning in Dynamic Multi-Attribute Tradespace Exploration," in *3rd Annual IEEE Systems Conference*, Vancouver, Canada, 2009.
- [125] A. Ross, "Managing unarticulated value: changeability in multi-attribute tradespace exploration," PhD in Engineering Systems, Cambridge, MA, 2006.
- [126] A. Ross and D. Rhodes, "Using natural," in *INCOSE International Symposium*, Utrecht, Netherlands, June 2008.
- [127] M. Curry and A. Ross, "Considerations for an Extended Framework for Interactive Epoch-Era Analysis," in *13th Conference on Systems Engineering Research*, Hoboken, NJ, 2015.
- [128] Michael Curry and Adam Ross, "Designing for System Value Sustainment using Interactive Epoch Era Analysis: A Case Study for On-orbit Servicing Vehicles," *Systems Engineering*, 2016.
- [129] A. Ross et al., "Responsive Systems Comparison Method: Case

- Study in Assessing Future Designs in the Presence of Change," in *AIAA Space*, San Diego, CA, 2008.
- [130] Zhicheng Liu and Jeffrey Heer, "The Effects of Interactive Latency on Exploratory Visual Analysis," in *Comp. Graphics (Proc. InfoVis)*, 2014.
- [131] S. and Spence, I. Lewandowsky, "Discriminating Strata in Scatterplots," *Journal of the American Statistical Association*, vol. 84, no. 407, pp. 682-688, September 1989.
- [132] L. Harrison, F. Yang, and S. and Chang, R. Franconeri, "Ranking Visualizations of Correlation Using Weber's Law," *IEEE Transactions on Visualization and Computer Graphics*, vol. 20, no. 12, pp. 1943-1952, November 2014.
- [133] Y. Fua, M. Ward, and E. Rundensteiner, "Hierarchical parallel coordinates for exploration of large datasets," in *VIS '99: Proceedings of the conference on Visualization '99*, San Francisco, CA, 1999, pp. 43-50.
- [134] J. Blaas, C. Botha, and F. Post, "Extensions of parallel coordinates for interactive exploration of large multi-timepoint data sets," *IEEE Transactions on Visualization and Computer Graphics*, vol. 14, no. 6, pp. 1436-1443, November 2008.
- [135] Synchronised Histograms with Menu-filter and Brush-filter. [Online]. <http://kyrandale.com/apps/#/hist-demo>
- [136] G. Robertson, R. Fernandez, D. Fisher, B. Lee, and J. Stasko, "Effectiveness of Animation in Trend Visualization," *IEEE Transactions on Visualization and Computer Graphics*, vol. 14, no. 6, pp. 1325-1332, November 2008.
- [137] J. G. Hollands and I. Spence, "Judging proportion with graphs: the summation model," *Applied Cognitive Psychology*, vol. 12, no. 2, pp. 173-190, April 1998.
- [138] I. Spence and S. Lewandowsky, "Displaying proportions and percentages," *Applied Cognitive Psychology*, vol. 5, no. 1, pp. 61-77, January 1991.
- [139] Michael Curry and Adam Ross, "Considerations for an Extended Framework for Interactive Epoch-Era Analysis," in *13th Conference on Systems Engineering Research*, Hoboken, NJ, March 2015.
- [140] Patrick Krolak, Wayne Felts, and George Marble, "A Man-Machine Approach Toward Solving the Traveling Salesman Problem," *Communications of the ACM*, vol. 14, no. 5, pp. 327-334, May 1971.
- [141] J. Thomas, C. Ken, and A. Leow, "An interactive approach to solve the Travelling Salesman Problem," in *2010 5th International Conference on Computer Sciences and Convergence Information Technology (ICCIT)*, 2010.
- [142] Jeffrey Heer and Michael Bostock, "Crowdsourcing Graphical Perception: Using Mechanical Turk to Assess Visualization Design," in

ACM Human Factors in Computing Systems (CHI), 2010, pp. 203–212.

- [143] Caroline Ziemkiewicz et al., "How Visualization Layout Relates to Locus of Control and Other Personality Factors," in *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, 2013, pp. 1109-1121.
- [144] Eli Brown et al., "Finding Waldo: Learning about Users from their Interactions," in *IEEE Transactions on Visualization and Computer Graphics*, vol. 20, 2014, pp. 1663 - 1672.
- [145] Alvitta Ottley et al., "Improving Bayesian Reasoning: The Effects of Phrasing, Visualization, and Spatial Ability," in *IEEE Transactions on Visualization and Computer Graphics*, vol. 22, 2015, pp. 529-538.
- [146] L. Micallef, P. Dragicevic, and J. Fekete, "Assessing the effect of visualizations on bayesian reasoning through crowdsourcing," in *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, 2012, pp. 2536–2545.
- [147] Christopher Mims. (2010, Jan) MIT Technology Review: How Mechanical Turk is Broken. [Online]. <https://www.technologyreview.com/s/416966/how-mechanical-turk-is-broken/>
- [148] Connor Huff and Dustin Tingley, "'Who are these people?' Evaluating the demographic characteristics and political preferences of MTurk survey respondents," *Research and Politics*, vol. 1, no. 12, pp. 1-12, July 2015, DOI: 10.1177/2053168015604648.
- [149] Joseph Henrich, Steven Heine, and Ara Norenzayan, "Most people are not WEIRD," *Nature*, vol. 466, no. 1, p. 29, July 2010.
- [150] David Sears, "College sophomores in the laboratory: Influences of a narrow data base on social psychology's view of human nature," *Journal of Personality and Social Psychology*, vol. 51, no. 3, pp. 515-530, Sept 1986.
- [151] Lane Harrison. (2016, June) Github: experimentr. [Online]. <https://github.com/codementum/experimentr>
- [152] C. Chen and M. Czerwinski, "Spatial ability and visual navigation: An empirical study. ," *New Review of Hypermedia and Multimedia*, vol. 3, no. 1, pp. 67-89, 1997.
- [153] D. Silver, and M. Tremaine M. C. Velez, "Understanding visualization through spatial ability differences," in *IEEE Visualization*, 2005, pp. 511-518.
- [154] H. Yang, and R. Chang. A. Ottley, "Personality as a predictor of user strategy: How locus of control affects search strategies on tree visualizations. ," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2015.
- [155] M. B. Donnellan, F. L. Oswald, B. M. Baird, and R. E. Lucas, "The miniipip scales: tiny-yet-effective measures of the big five factors of personality," *Psychological assessment*, vol. 18, no. 2, p. 192, 2006.
- [156] L. R. Goldberg et al., "The international personality item pool and

- the future of public-domain personality measures," *Journal of Research in Personality*, vol. 40, no. 1, pp. 84-96, 2006.
- [157] Sandra Hart and Lowell Staveland, "Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research," *Advances in Psychology*, vol. 52, pp. 139-183, Dec 1988.
- [158] K. Schloss, and D. Laidlaw C. Gramazio, "The relation between visualization size, grouping, and user performance," *IEEE Transaction on Visualization and Computer Graphics*, vol. 20, no. 12, pp. 1953-1962, Dec 2014.
- [159] Robert Jacob, "Designing Brain-Computer Interfaces for Intelligent Information Delivery Systems," Computer Science, Tufts University, Medford, MA, Phd Thesis 2014.
- [160] Nicola Ricci, Michael Schaffner, Adam Ross, Donna Rhodes, and Matthew Fitzgerald, "Exploring Stakeholder Value Models Via Interactive Visualization," in *12th Conference on Systems Engineering Research*, Redondo Beach, CA, March 2014.
- [161] Rudolf Smaling and Olivier de Weck, "Fuzzy Pareto Frontiers in Multidisciplinary System Architecture Analysis," in *10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, Albany, NY, September 2004.
- [162] Daniel Fulcoly, Adam Ross, and Donna Rhodes, "Evaluating System Change Options and Timing using the Epoch Syncopation Framework," in *10th Conference on Systems Engineering Research*, St. Louis, MO, March 2012.
- [163] Dana Nau, "Pathology on Game Trees Revisited, and an Alternative to Minimizing," *Artificial Intelligence*, vol. 21, no. 1-2, pp. 221-244, 1983.
- [164] Carl Rehn et al., *Ill-Structured Commercial Ship Design Problems: The Responsive System Comparison Framework on an Offshore Vessel Case*, Working Paper, Ed. Cambridge, MA, USA: Massachusetts Institute of Technology, 2016.
- [165] Jose Jorge Garcia Agis, Ulrikke Brask Brandta, and Per Olaf Brett, "Unintentional consequences of the golden era of the Offshore Oil & Gas industry," *International Conference on Ships and Offshore Structures*, September 2016.
- [166] S. O. Erikstad and C. F. Rehn, "Handling Uncertainty in Marine Systems Design," in *12th International Marine Design Conference (IMDC) 2015*, Tokyo, Japan, 2015.
- [167] S. S. Pettersen, C. F. Rehn and A. Ebrahimi J. J. Garcia, "Handling Commercial, Operational and Technical Uncertainty in Early Stage Offshore Ship Design," in *Conference on System of Systems Engineering*, Kongsberg, Norway, 2016.
- [168] M. Curry, C. Rehn, A. Ross, and D. Rhodes, "Designing for System

Value Sustainment using Interactive Epoch-Era Analysis: A Case Study from Commercial Offshore Ships," in *Conference on Systems Engineering Research*, Redondo Beach, CA, 2017, March 23-25.

- [169] Matthew Fitzgerald, "Framing Tradespace Exploration to Improve Support for Multiple-Stakeholder Decision Making," Aeronautics and Astronautics, Massachusetts Institute of Technology, Cambridge, MA, PhD Thesis 2016.
- [170] S., Ayres, P., Chandler, P., & Sweller, J. Kalyuga, "The expertise reversal effect," *Educational Psychologist*, vol. 38, pp. 23-31, 2003.
- [171] (2017, May) Wikipedia: Office Assistant. [Online]. https://en.wikipedia.org/wiki/Office_Assistant
- [172] P. Krolak, W. Felts, and G. Marble, "A Man-Machine Approach Toward Solving the Traveling Salesman Problem," *Communications of the ACM*, vol. 14, no. 5, May 1971.
- [173] Linkoping University. Parallel Coordinates and Radar Chart. [Online]. <http://ncva.itn.liu.se/education-geovisual-analytics/parallel-coordinates-and-radar-chart?l=en>
- [174] Rosen P. Nguyen H, "DSPCP: A Data Scalable Approach for Identifying Relationships in Parallel Coordinates," in *IEEE Transactions on Visualization and Computer Graphics*, 2017.
- [175] LMN Architects. (2015, February) Interacting with Climate Data. [Online]. <http://lmnarchitects.com/tech-studio/wp-content/uploads/sites/4/2014/04/Climate/epw-6hour.html>
- [176] A. Ross, H. McManus, D. Rhodes, D. Hastings, and A. Long, "Responsive Systems Comparison Method: Dynamic Insights into Designing a Satellite Radar System," in *AIAA Space 2009*, Pasadena, CA, 2009.
- [177] A. Ross, H. McManus, D. Rhodes, and D. Hastings, "A role for interactive tradespace exploration in multi-stakeholder negotiations," in *AIAA Space*, Anaheim, CA, 2010.
- [178] P.C. Wong and J. Thomas, "Visual Analytics," *IEEE Computer Graphics and Applications*, vol. 24, no. 5, pp. 20-21, 2004.
- [179] I. Icke and E. Sklar, "Visual Analytics: A Multi-faceted Overview," 2009.
- [180] D. Keim, "Information visualization and visual data mining," *IEEE Transactions on Visualization and Computer Graphics*, vol. 8, no. 1, pp. 1-8, 2002.
- [181] J. Heer and B. Shneiderman, "Interactive Dynamics for Visual Analysis," in *ACM Queue*, 2012.
- [182] D. Keim et al., "Visual Analytics: Definition, process, and challenges," in *Information Visualization*, 2008, pp. 154-175.
- [183] J. Heer and M. Agrawala, "Design considerations for collaborative visual analytics," *Information Visualization*, vol. 7, no. 1, pp. 49-62, 2007.

- [184] R. Smaling, "Fuzzy Pareto Frontiers in Multidisciplinary System Architecture Analysis," in *10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, Albany, NY, 2004.
- [185] Ying Zhu, "Measuring Effective Data Visualization," in *3rd International Symposium on Visual Computing*, Lake Tahoe, CA, 2007.
- [186] E. Spero, C. Bloebaum, B. German, A. Pyster, and A. Ross, "A Research Agenda for Tradespace Exploration and Analysis of Engineered Resilient Systems," in *13th Conference on Systems Engineering Research*, Redondo Beach, CA, 2014.
- [187] Masato Inoue et al., "Decision-making support for sustainable product creation," *Advanced Engineering Informatics*, vol. 26, no. 4, pp. 782-792, 2012.
- [188] Jeffrey Holland, Engineered Resilient Systems, October 2014.
- [189] S. Goerger, A. Madni, and O. Eslinger, "Engineered Resilient Systems: A DoD Perspective," in *12th Conference on Systems Engineering Research*, Redondo Beach, CA, CA, 2014.