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SUPPORTING TRADE SPACE EXPLORATION OF MULTI-DIMENSIONAL DATA WITH INTERACTIVE MULTI-SCALE NESTED CLUSTERING AND AGGREGATION

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ABSTRACT

Knowledge discovery in multi-dimensional data is a challenging problem in engineering design. For example, in trade space exploration of large design data sets, designers need to select a subset of data of interest and examine data from different data dimensions and within data clusters at different granularities. This exploration is a process that demands both humans, who can heuristically decide what data to explore and how best to explore it, and computers, which can quickly identify features that may be of interest in the data. Thus, to support this process of knowledge discovery, we need tools that go beyond traditional computer-oriented optimization approaches to support advanced designer-centered trade space exploration and data interaction. This paper is an effort to address this need. In particular, we propose the Interactive Multi-Scale Nested Clustering and Aggregation (iMSNCA) framework to support trade space exploration of multi-dimensional data common to design optimization. A system prototype of this framework is implemented to allow users to visually examine large design data sets through interactive data clustering, aggregation, and visualization. The paper also presents a case study involving morphing wing design using this prototype system. By using visual tools during trade space exploration, this research suggests a new approach to support knowledge discovery in engineering design by assisting diverse user tasks, by externalizing important characteristics of data sets, and by facilitating complex user interactions with data.

1. INTRODUCTION

Complex engineered systems such as automobiles, aircraft, and satellites usually consist of multiple, interacting subsystems and components that are often designed by engineers from a variety of disciplines. The main challenge when designing such systems lies in resolving the inherent tradeoffs that exist both within and between subsystems and the overall system. For example, an aircraft is composed of the wings, fuselage, engines, and countless other subsystems and components. If we consider the design of the wings, tradeoffs exist between aerodynamics, structures, and controls among others, yet wing designers must also reduce the weight of the wing to help minimize the overall weight of the aircraft.

The design of such complex engineered systems is preparing for a paradigm shift. More and more, designers want to go beyond single point solutions obtained from a fully automated optimization process, and explore trade space while "shopping" for the best design that suits their needs and meets the customers' requirements. This paradigm shift from design *optimization* to design *exploration* is being enabled by recent advances in computing power/ speed and novel visualization tools; however, designers are encountering new problems such as information overload in that they have too many options from which to choose and become overwhelmed, not knowing which design is the best. Trade space here refers to the "potential solution space" [1]. This space consists of a set of multiple design alternatives, data attributes, or system parameters that designers can evaluate to satisfy various design objectives [2]. For example, in vehicle design, design parameters like car size, engine type, and torque are considered together under a set of design objectives (e.g., fuel efficiency, performance). All possible value combinations of these parameters make a trade space for design.

Designers need help in analyzing large data sets and generate knowledge from them. Usually, large data sets are multi-dimensional and stored in databases, and designers often choose part of a data set in certain dimensions and examine their behaviour in other dimensions. For example, one of the primary challenges in the design of complex engineered systems, such as aircraft, is to identify interesting trends among many design alternatives. Designers explore multiple design alternatives to evaluate the impact of changes in the wing parameters (e.g., aspect ratio, span, materials) on the

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performance of the aircraft (e.g., range, take-off weight, cost). To determine the best design(s) among thousands of simulated design alternatives – created by varying these design variables and storing the corresponding values of the performance variables for each alternative – designers need to compare the performance of each alternative to choose the best design variables. Designers need effective tools for choosing data of interest (often a subset of the whole data set), selecting the attributes to observe (e.g., aspect ratio in the aforementioned example), and determining which attributes to cluster during data analysis (e.g., gross weight, material type). Furthermore, designers would benefit greatly from controlling the way in which they compare design alternatives, such as evaluating data clusters with different aggregation methods (e.g., mean, median, sum) and changing the size of clusters. Current data analyses and visualization tools in engineering design do not support these diverse needs well. Advanced visualization techniques like the scatter plot matrix [3] are largely *ad hoc* and often overwhelm designers with too much information.

To support trade space exploration for multi-dimensional data, we propose an Interactive Multi-Scale Nested Clustering and Aggregation (iMSNCA) framework in this paper. The novel framework puts design activities in the forefront and emphasizes the role of computational tools in supporting such activities by considering the characteristics of design data. The next section reviews relevant literature, and then Section 3 introduces the framework, and a prototype system is described in Section 4. A case study involving an aircraft wing design problem is presented in Section 5. Finally, the benefits and limitations of this research are discussed in Section 6.

2. RELATED WORK

The research presented in this paper relates to trade space exploration in engineering design, scientific and information visualization, and multi-dimensional and multi-scale data interaction. Each is reviewed in the following sections.

2.1. Visualization in Engineering Design

Much of the research in the design of complex engineered systems has focused on novel formulations and algorithms for solving optimization problems (e.g., [4, 5, 6]); approximation methods to reduce the computational expense of these analyses (e.g., [7, 8]); and computational frameworks to integrate analyses from multiple disciplines (e.g., [9, 10]). Despite the advances and developments over the past two decades, design optimization still has several shortcomings and challenges [11]. Balling [12] has noted that the traditional optimization-based design process of "(1) formulate the design problem, (2) obtain/develop analysis models, and (3) execute an optimization algorithm" often left designers unsatisfied with their results because the problem is usually improperly formulated: "the objectives and constraints used in optimization were not what the owners and stakeholders really wanted…in many cases, people don't know what they really want until they see some designs". Similar findings have occurred in other fields. For instance, Shanteau [13] observed that when people are dissatisfied with the results of a rational decision-making process, they often change their ratings to make it come out the way they want. Wilson and Schooler [14] have shown that people do worse at some decision tasks when asked to analyze the reasons for their preferences or to evaluate all the attributed of their choices.

Consequently, there is an emerging paradigm of design exploration whereby designers "shop" for the best solution using visualization tools instead of relying solely on optimization. This Design by Shopping process, introduced by Balling [12], allows designers to explore the design space first and then choose an optimal solution from a set of possible designs after "forming realistic expectations of what is possible". This approach can be classified as an *a posteriori* articulation of preferences to solve a multi-objective optimization [15] in that designers first form their preferences based on visualization of the entire design space, and then choose an optimal design that is based on their formed preference. The basic steps to such an approach include: (1) creating a simulation model to analyze the system being designed, (2) generating thousands of simulated design alternatives by varying design variables and storing the corresponding values of the performance variables for each alternative, and (3) using visualization tools to explore these design alternatives and "shop" for the best design [16].

To date, trade space exploration has focused primarily on developing virtual environments and visualization tools to support such an approach. For instance, spherical mechanism design has benefited greatly from virtual reality advancements [17, 18], as have large-scale manufacturing simulations [19, 20]. Several researchers have also looked at effective interface development for virtual environments [21, 22]. Virtual reality has supported a wide variety of engineering design problems [23]; however, such environments tend not to support trade space exploration since they are used to visualize a single point solution, not explore the entire trade space. Cloud Visualization [24], the Visual Design Steering methods [25, 26], the ATSV system [27, 28], and the U.S. Naval Research Laboratory's visual steering methods in their Virtual Reality Lab and High Performance Computing Center [29] are exceptions to this, but these methods are used in an *ad hoc* manner to support design decision-making – none of the research in engineering design has investigated the knowledge discovery process during trade space exploration or formalized systematic procedures to support it. Meanwhile, efforts to simplify the visualization of n-dimensional Pareto frontiers [30] and group uncertainty-related data into "bricks" [31] provide good intentioned, yet still ad hoc, solutions to the problem of overwhelming designers with too much information as they are put "back in the loop" as part of the trade space exploration process.

2.2. Scientific and Information Visualization

Research on using visualization to facilitate information and knowledge processing has advanced greatly in the past two decades. Card, et al. [32] classify visualization techniques into two categories – scientific visualization and information visualization – based on the nature of the data being visualized. Scientific visualization usually deals with physical data. In scientific visualization projects, such as flow vector visualization [33, 34, 35], the spatial relationship of physical objects is accurately mapped (often re-scaled to fit the screen), into that of visual components so that scientific phenomena can be accurately measured and clarified. Information visualization extends beyond physical data and usually focuses on helping people analyze and making sense of more abstract phenomena. For example, Card, et al. [36] proposed a 3D-based visualization technique for information visualization where the 3D space is used to expand people's information workspace and reduce the cognitive costs in dealing with complex data, rather than just as a habitat to show 3D data.

Information visualization also provides a means for exploratory analysis [37]. While scientific visualization emphasizes confirmatory analysis (i.e., confirm or reject hypotheses), information visualization can also help people identify new hypotheses through cognitive amplification and user-centered interactive designs [32]. Cognitively, visualizing information benefits users by increasing available spatial (e.g., large workspace) and cognitive resources (e.g., less demand for information recall mentally), improving searching processes (e.g., color-coded visual search), enhancing pattern recognition (e.g., visual icons), etc. Interactively, information visualization allows users to manipulate the data transformation from raw data (e.g., direct manipulation), control the mapping between data and visual forms (e.g., hierarchical visualization as discussed later), and modify the views on visual forms (e.g., zooming). Cognitive amplification and flexible interaction facilitate a knowledge crystallization process that provides "the most compact description possible" of complicated data and information [32].

Making sense of large data sets often involves creating structures and putting data into structures [38], and this "sense-making" process is often a critical component in the knowledge crystallization process. The famous "knowledge hierarchy" of Lucky [39] argues that knowledge is built upon information, which is in turn built upon data. In this sense, knowledge is the result of aggregating information, and knowledge discovery arises from organizing fragmental information into structured knowledge schemas. However, finding appropriate structures to organize available information is a complicated yet cognitively costly process, because possible structures must be mentally searched and modified to fit all information of interest. Such searching and fitting activities are conceptual and involve analysis of the attributes of both knowledge structures and information pieces. To reduce the cognitive costs of "sense-making", researchers have proposed a variety of structures for organizing information [40]. Among these structures, hierarchies are frequently used to organize information and knowledge: they provide semantic descriptions with different levels of detail and allow users to navigate through the different levels with context and content as needed. Techniques for visualizing hierarchies include Treemaps [41], Cone Trees [42], and Hyperbolic views [43], which use nested boxes, 3D space and interactive animation, and hyperbolic representations, respectively.

Although information visualization is regarded as a means to crystallize knowledge, visualization-based methods to support knowledge discovery in engineering design are not well understood. Among the extensive literature on information visualization, we are particularly interested in research on multi-dimensional and multi-scale data visualization, because design data for complex engineered systems is usually multi-dimensional and designers often need to examine data at different levels of analysis when designing different sub-systems.

It should be noted that data visualization is a broad topic that has been researched by scientists from many disciplines. For example, researchers in statistics also have developed powerful tools to assist the analysis of multi-dimensional data [44, 45]. However, these tools are often built upon specialized statistics software packages (e.g., R), making it impractical to integrate them into general-purpose, stand-alone visualization systems. Also, the focus of such tools is on visualizing general statistical characteristics of large data sets, and need to be further enhanced to support trade space exploration, which often concerns both general data distributions of data at a global level and potential data anomalies at local levels.

2.3. Multi-Dimensional and Multi-Scale Interactions

Extensive research has been done in visualizing multi-dimensional data. Although these techniques are not targeted at in-depth analysis, such as quantitatively comparing a few dimensions, their focus on visualizing overall relationships does serve as the entry point to understanding of multi-dimensional data. Parallel coordinates [46] represent individual dimensions as parallel lines, and plot a multi-dimensional record as a poly-line across parallel coordinates, revealing cross-dimension patterns and trends. There are also some variations derived from this technique [47] by positioning individual dimensions in different ways. These techniques are effective to present overall trends, but lack detailed descriptions of between-dimension relationships and aggregated information of individual dimensions. Scatter plot matrices [3] use a matrix to organize scatter plots between each pair of dimensions and helps users quickly grasp the overall trends and relationships between each pair of dimensions and then pick those of interest. Recently, this technique was improved by the Rank-By-Feature [48] method, which color-codes the matrix cells based on the magnitude of correlation between each pair of dimensions. However, these techniques largely focus on between-dimension relationships, and they do not provide sufficient support for detailed analysis within dimensions of interest. The Table Lens technique [49] uses a simple 2D table to hold data for in-depth, within-dimensional data analysis, but the tools are largely about ranking and sorting data, which are not sufficient for engineering design. Some commercial software packages (e.g., Tableau and ILOG) provide comprehensive tools for multi-dimensional data visualization. However, their support for in-depth data analysis within the same dimension is insufficient to enable designers to examine how designs may vary at different levels of analysis.

Multi-scale user interfaces, also called zoomable user interfaces, allows users to control the levels of detail in visualizing and interacting with large data sets. Benefits of multi-scale tools include helping users obtain desired context and content information and showing important characteristics of data at various scales at the same workspace [50, 51, 52]. However, most systems that use multi-scale tools, such as PhotoMesa [53], are targeted for data sets that are already hierarchically structured. Few designs can support interaction with raw data sets that do not have hierarchical structures or are not structured at all.

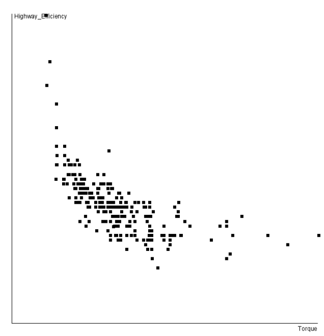
Semantic zooming is a powerful tool in multi-scale user interfaces for visualizing different data properties across scales. For example, with semantic zooming, designers can examine what factors affect the characteristics of a new material by seeing features from the atomic level (e.g., the strength of atomic bonds) to the microscopic level (e.g., the tangle of molecules) to the macroscopic level (e.g., mechanical stress). However, how to generate semantic representations across scales is still a challenge. Some efforts have been made to interactively construct semantic representations for a small set of objects [54], but it is still difficult to deal with large data sets with thousands or even millions of data records.

3. THE INTERACTIVE MULTI-SCALE NESTED CLUSTERING AND AGGREGATION (IMSNCA) FRAMEWORK

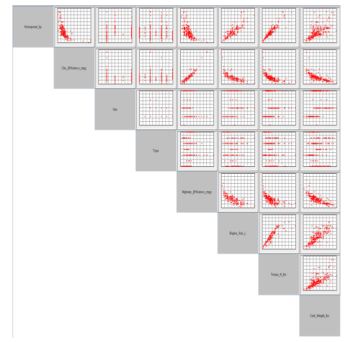
The iMSNCA framework guides the visualization of multi-dimensional data and supports multi-scale analysis. It is developed based on our observations of the design of complex engineering systems that involve extensive use of simulation-based design and struggle with visualizing the results.

3.1. Framework Development

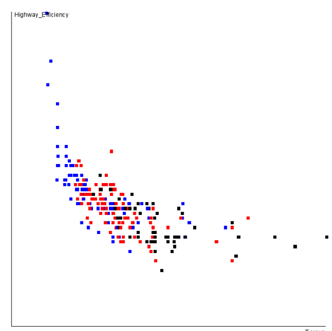
When designers visualize large data sets, one of the primary goals is to identify interesting trends among thousands, if not millions, of design alternatives. For vehicle design, for instance, we may be interested in understanding how size, geometry, engine type, etc. affect vehicle performance characteristics such as torque, fuel efficiency, MSRP, etc. Designers might also want to know how these performance characteristics are correlated; so, a design might, for instance, construct a scatter plot of available design alternatives to see how torque and highway_efficiency (see Figure 1a). From this figure, the designer might see that the points tend to concentrate in the middle torque region, and a savvy designer might want to explore the data more to identify how this relates to the size of the car (i.e., compact, midsize, large). After viewing the scatter matrix in Figure 1b, the values can be grouped and color-coded by size to create Figure 1c, which provides insight among three groupings: designs in a size group with lower torques (blue) lead to better results than those in the other two groups with higher torques (red and black). The designer can view these three size groups in more detail by comparing the average highway_efficiencies for each group as seen in Figure 1d. During the exploration, the designer can change the viewing scale of any graph at any time to see general patterns or detailed data.



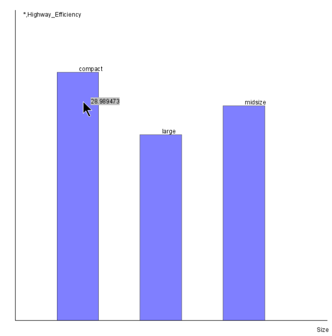
a: Initial scatter plot



b: Correlation scatter matrix



c: Plot color-coded by type



d: Highway_efficiency average

Figure 1: Car design tradeoff example

This hypothetical exploration process demonstrates several major tasks in the trade space exploration process. First, the designer selects three data dimensions (i.e., highway_efficiency, torque, and size) from those available and then clusters the data based on the dimension(s) of interest (size in this case). Next, the designer uses different graph types, a scatter plot and a histogram in this case, to compare data clusters of interest. Some graph types (e.g., histogram) show the aggregate descriptions of data clusters, while some (e.g., scatter plot) do not. Finally, the designer explores design alternatives at different levels of analysis by manipulating the viewing scale of the graphs (e.g., zooming out on the scatter matrix to browse the overall pattern or zooming in the matrix to examine the relationship between any two dimensions).

Based on these observations and a visualization model by Card, et al. [32], we propose the iMSNCA framework shown in Figure 2. This framework elaborates data objects (rounded-squares) and user tasks (ovals) involved in interactive processes of trade space exploration. In the following sections, these tasks are briefly introduced. Detailed descriptions on the algorithms of key task components of this framework can be found in Section 4.

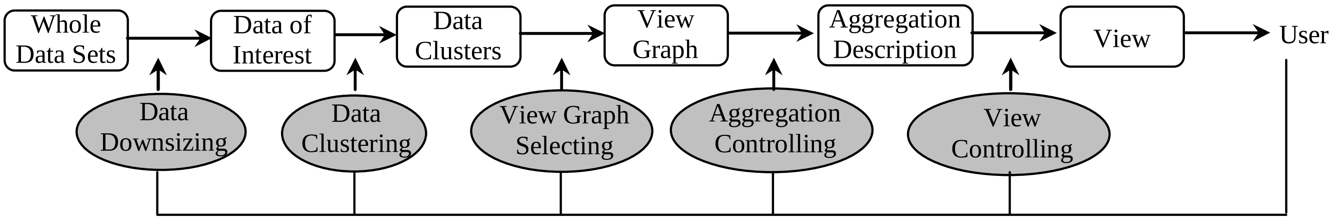


Figure 2: iMSNCA framework for engineering design

3.2. iMSNCA Framework Tasks

3.2.1. Data Downsizing

There are some benefits to using downsized tables. One of them is to reduce the size of the data that is subsequently processes, such as visual mapping and view transformation, have to handle. In particular for large data sets with hundreds or even thousands of dimensions, a downsized table can dramatically reduce the burden of machine processes and accelerate visualization speed. Also, with downsized data, unwanted dimensions and information corresponding them can be eliminated on screen, releasing more screen space for important data.

A designer usually relies on data management tools to downsize data. Using a database, for example, the designer has to know how to create tables or index for data subsets. Thus, the designer also needs to master data management tools in trade space exploration. It would be beneficial to integrate interactive tools that can automatically create data subsets based on user actions, with visualization tools.

3.2.2 Data Clustering

Clustering in this case refers to a task that groups data records based on their values in certain dimensions of interest. When a designer is interested in multi-dimensional data, clusters on different dimensions are often needed. Take the aforementioned aircraft wing example: the designer wants to know the impact of each design variable, or each dimension of data, on design. It is needed to examine how different values of a dimension may affect the outcomes of design as well as how these dimensions together may affect designs. Thus, the designer needs tools to cluster data in different dimensions.

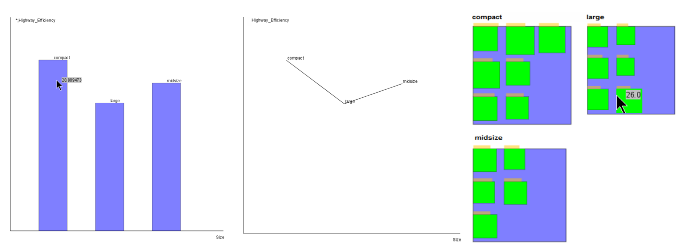
We refer to the clustering of data on multiple dimensions as *multi-dimensional clustering*. Multiple dimensions can be used to cluster the data in different ways. They can be chosen in a *serial* manner, one dimension after the other, or in *parallel*, several dimensions chosen together. For example, suppose two design factors – Gross Weight and Material Type – are of interest in the wing design example. With a series multi-dimensional clustering approach, the designer first clusters design alternatives according to their Gross Weight *or* Material Type first, and then subclusters by the other dimension. Parallel clustering creates clusters according to Gross Weight *and* Material Type together.

The designer often groups data at different scales as well. Larger yet coarser clusters contain more data and can provide a high level of abstraction, while smaller and finer clusters contain less data but provide more accurate information on individual records. Such *multi-scale clustering* is important, because large clusters can help the designer identify trends and find which clusters to focus on, while small clusters can provide more concrete evidence of trends. With multi-scale clustering, the designer can shift between detailed information on individual design alternatives while maintaining a good overall understanding of how alternatives in different clusters may be different from each other. The designer can benefit from tools that support interactive control over data clustering dimensions and if multiple dimensions are involved, the way these dimensions should be linked.

It should be noted that data downsizing and data clustering serve for different purposes in our framework. Both tasks can reduce the amount of data and information users have to deal with, but they achieve this goal in different ways. Data downsizing reduces data amount by eliminating those data dimensions that users are not interested in, while data clustering aggregates data points that share common features so that users will see a small set of data groups rather than a large amount of fragmental data points.

3.2.3. View Graph Selection

Various kinds of view graphs can be used in data visualization; however, choosing an appropriate graph type is important for cognition [32]. Figure 3 shows three different types of view graphs used by a designer to compare averages of three groups. Different view graphs can serve different purposes in knowledge exploration. For example, the designer can choose a histogram (see Figure 3a) to compare categorical data or a line graph (see Figure 3b) for ratio or scale data. To explore the characteristics of sub-clusters within clusters, Figure 3c would be better because sub-clusters can be shown as boxes nested inside their parent cluster box. Thus, allowing the designer to choose different graph types is important.



(a) (b) (c)

Figure 3: Different view graphs for visual comparison

3.2.4. Aggregation Control

To compare clustered data, the designer can uses aggregation tools to acquire descriptive information about how clusters differ from one to another. Data can be aggregated in different ways. Often seen aggregation methods include the

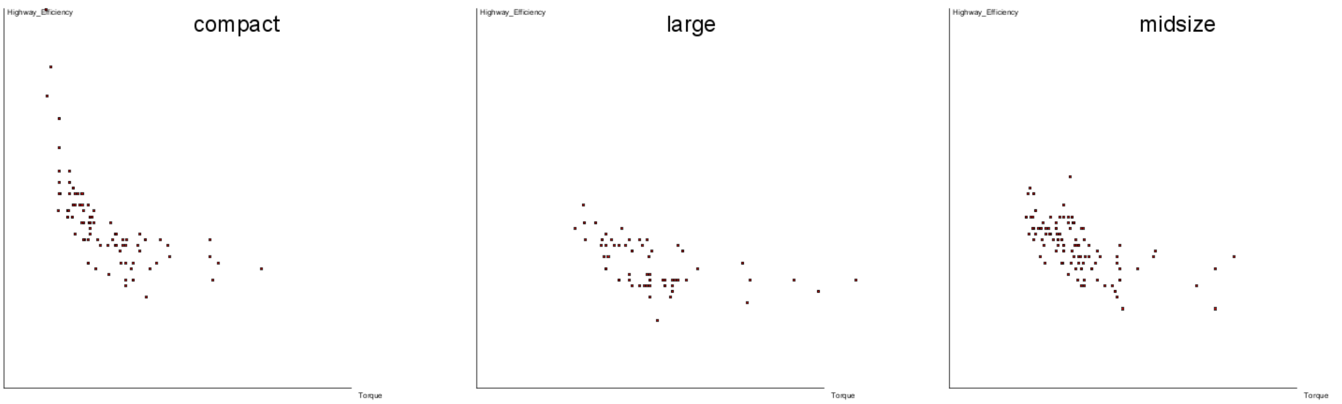


Figure 4: Separated scatter plots of three size clusters

total count of records, the average, median, and sum of data of interest, the maximum and minimal values of data, and so on. It would also be desirable to let the designer choose different data aggregation methods.

3.2.5. View Control

The designer can control the view of view graphs by panning or zooming. Where we are interested here is the zooming tool that can change the size of view objects as well as data clusters. With zooming, the designer can easily move from the color-coded scatter plot in Figure 1c, which shows a general pattern but is still cluttered, to a view that is easy to compare different clusters side by side (see Figure 4).

When data is clustered under two dimensions, the designer can zoom in the graph seen in Figure 1c and see scatter plots in two dimensions. Figure 5 shows such two-dimensional scatter plots organized as a spreadsheet [55], in which the values of Gross Weight change horizontally and those of Material Type change vertically. The designer can compare design options in two dimensions simultaneously.

Changing the view scale from Figure 1c to Figure 4 or from Figure 1c to Figure 5 also implies a scale change for data clustering since the levels of the data clusters visualized in Figure 4 and Figure 5 are different from that of the data cluster in Figure 1c. Thus, the notion of scale in our iMSNCA framework differs from the concept of scale in traditional multi-scale user interfaces, which is usually regarded as a measure of the rendered size of objects [50, 51]. Scale in our framework is a measure of interaction activities that include both data clustering and graph viewing. Zooming here is a tool to resize visual objects as well as a means to control the level of data clustering.

Although research on trade space exploration has studied most of these data manipulation tasks [27, 56, 57, 58, 59], it is rare to see systems to support engineering design with interactive data clustering across different scale levels of analysis. This research investigates the design, implementation, and application of the proposed approach.

4. PROTOTYPE DESIGN AND IMPLEMENTATION

To test the proposed framework, a prototype system is developed. In this section, we introduce the analytical forms of data downsizing, clustering, and aggregating, and describe the design and implementation of the system. Analytic forms are developed to provide a formal definition for downsizing, clustering, and aggregating tasks and to guide their implementation.

4.1. Analytic Forms for Data Transform

Let us define a raw data set D with n-dimensions:

$$A = \{a_1, a_2, \ldots, a_n\} \tag{1}$$

where A is the set of all dimensions; a_i is one dimension; and n is the total number of dimensions. Any data record in the data set is:

$$d = (da_1, da_2, \ldots, da_n) \tag{2}$$

where da_i is the value of the record on the a_i dimension. Then, the data set can be written as:

$$D = \{d_1, d_2, \ldots, d_m\} \tag{3}$$

where d_i is one record, and m is the total number of records.

Downsizing: Downsizing is a task to generate a subset, D_s, out of D. D_s is written as:

$$\begin{aligned} &A^s = \{a^s_i \mid a^s_i \in A,\ i=1,2, \ldots, k\} \\ &d^s = (da^s_1, da^s_2, \ldots, da^s_k) \\ &D_s = \{d^s_1, d^s_2, \ldots, d^s_m\} \end{aligned} \tag{4}$$

where A^s is the set of all dimension chosen for a data table; a^s_i is its member; k is the total number of its members; d^s is a data record of the subset D_s; and da^s_i is its value on the a^s_i dimension.

Clustering: Assume all possible values of a dimension a_i make up a set, Va_i. k clusters can be created on the dimension, and the value ranges of each cluster are defined as sets V_i, $i=1..k$.

Assume a_c is the clustering dimension. Then, a cluster is:

$$\begin{aligned} &C_i = \{d^s \mid d^s{}_{a_c} \in V_i\} && i=1, \ldots, k \\ &V_i \subset Va_c,\ \Sigma V_i \subset Va_c && i=1, \ldots, k \\ &V_l \cap V_m = \phi && l,m=1, \ldots, k,\ l \neq m \end{aligned} \tag{5}$$

where C_i is a cluster.

Multi-Dimensional Clustering: Multi-dimensional data clustering chooses different a_c. For *parallel* multi-dimensional clustering, multiple dimensions are applied at once. Assume

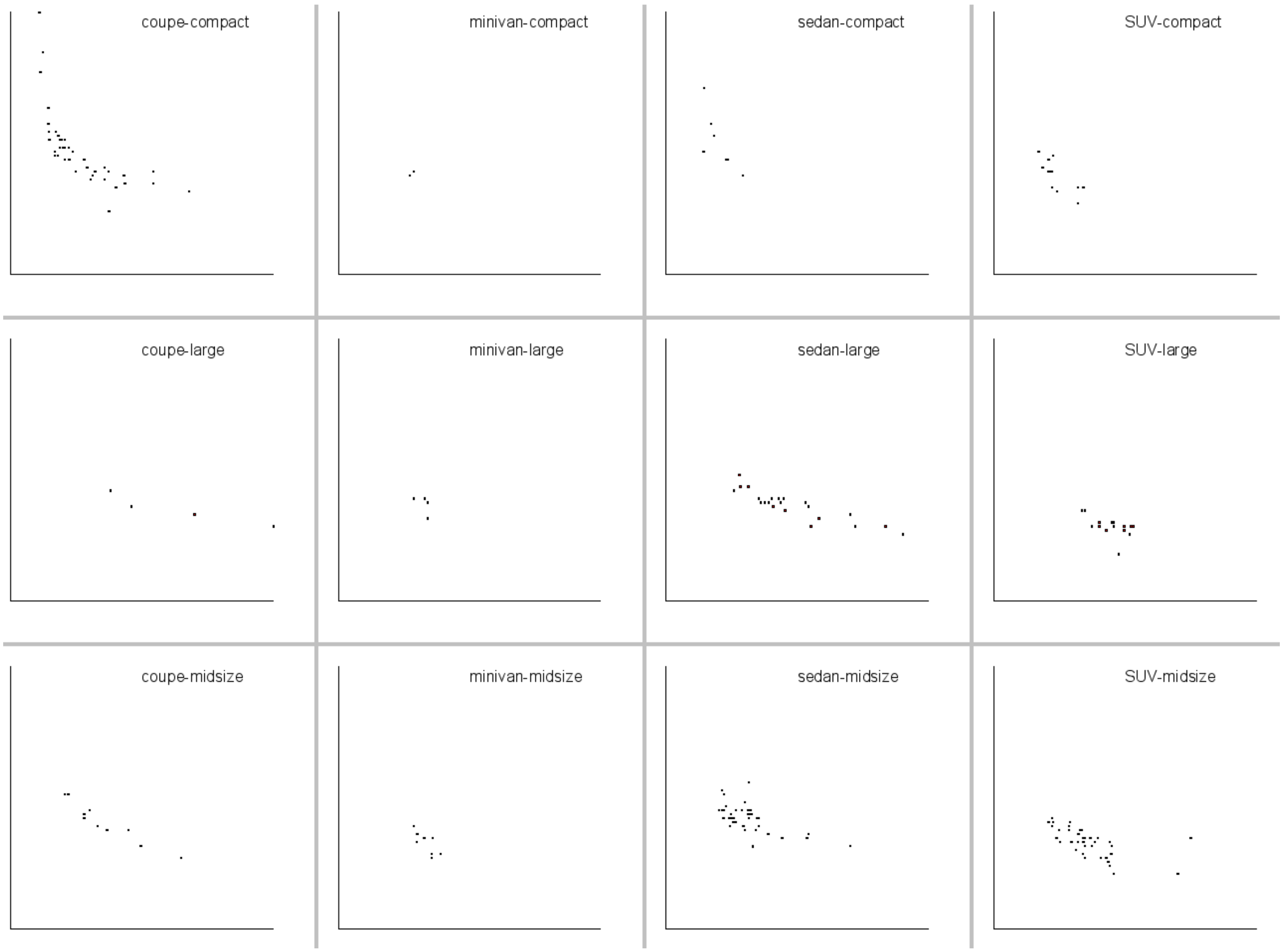


Figure 5: Part of Scatter Plots Matrix on Size and Type

two clustering dimensions are a_{c1} and a_{c2} and the numbers of data clusters on each individual dimension are k^1 and k^2, respectively. A cluster C_l under this parallel multi-dimensional clustering is:

$$
\begin{aligned}
&C_l = \{d^s \mid d^s{}_{a_{c1}} \in V^1{}_i \text{ and } d^s{}_{a_{c2}} \in V^2{}_j\} \\
&\qquad i=1,\ldots,k^1,\ j=1,\ldots,k^2, l=1,\ldots,k^1 \times k^2 \\
&V^1{}_i \subset Va_{c1}\ ,\ \Sigma V^1{}_i \subset Va_{c1} \qquad i=1,\ldots,k^1 \\
&V^1{}_l \cap V^1{}_m = \phi \qquad l,m=1,\ldots,k^1,\ l \neq m \qquad (6) \\
&V^2{}_i \subset Va_{c2}\ ,\ \Sigma V^2{}_i \subset Va_{c2} \qquad i=1,\ldots,k^2 \\
&V^2{}_l \cap V^2{}_m = \phi \qquad l,m=1,\ldots,k^2,\ l \neq m
\end{aligned}
$$

Multi-dimensional clustering with more clustering dimensions can be defined similarly.

As shown, the number of data clusters created in our method is based on a user-specified number. For discrete variables, such as categorical variables, this number can be determined by the number of all possible values and data clusters can be created by group data with similar values. For continuos variables, this number can be specified by users and then clusters can be created with *k*-mean algorithms.

Multi-Scale Clustering: For multi-scale data clustering, a cluster may have sub-clusters. Assume a cluster C_i is further divided into q sub-clusters according a clustering dimension a'_c, and the value ranges of each sub-cluster are defined as sets V'_j, $j=1..\ q$. Then, all of the sub-clusters of C_i can be written:

$$
\begin{aligned}
&C_{i,j} = \{d^s \mid d^s{}_{a'_c} \in V'_i\} \qquad j=1,\ldots,q \\
&V'_i \subset Va'_c\ ,\ \Sigma V'_j \subset Va'_c \qquad i=1,\ldots,k \qquad (7) \\
&V'_l \cap V'_m = \phi \qquad l,m=1,\ldots,k,\ l \neq m
\end{aligned}
$$

where $C_{i,j}$ is a sub-cluster within the cluster C_i. In this multi-scale clustering, clustering dimensions at different scale, a'_c and a_c, could be same or different.

Aggregating: With data clusters, aggregation can be done easily as long as the dimension(s) that would be aggregated and the aggregation functions are known or specified. Assume the dimension to aggregate a_g, for a particular cluster C_i, its aggregated description is:

$$G_i=F(d^c{}_{1|}a_g,\ d^c{}_{2|}a_g,\ldots,\ d^c{}_{p|}a_g) \quad (8)$$

where G_i is the aggregated value of C_i; F is the specified aggregation function; $d^c{}_{i|}a_g$ is the value of the ith of C_i on the dimension of a_g; and p is the total number of elements in C_i.

4.2. User Interface Design

Figure 6 shows the overall user interface of the prototype system after a designer provides information about the database and table where the data of interest is stored. The user interface has eight panels. Panels 1 to 5 are for data control. When raw data is ported into the system, the names of all data dimensions are displayed in Panels 1 and 3 for the designer to choose what dimensions to observe (Panel 1) and to what dimensions data are clustered (Panel 3). In Panel 2, the designer can choose aggregation methods (e.g., simple count, average, sum). Panels 4 and 5 allow the designer to choose data filtering and color-coding dimensions. Panel 6 provides the designer with different view graphs.

Panels 7 to 9 are for results display and interactive view control. Panel 7 shows view graphs and allows the designer to zoom and pan workspace as well as to choose different graphs. Panel 8 is a scale canvas that shows the viewing scale and allows the designer to manipulate the clustering order when multiple clustering dimensions are involved, which we will provide more details later. Panel 9 displays the data results in text corresponding different analysis operations.

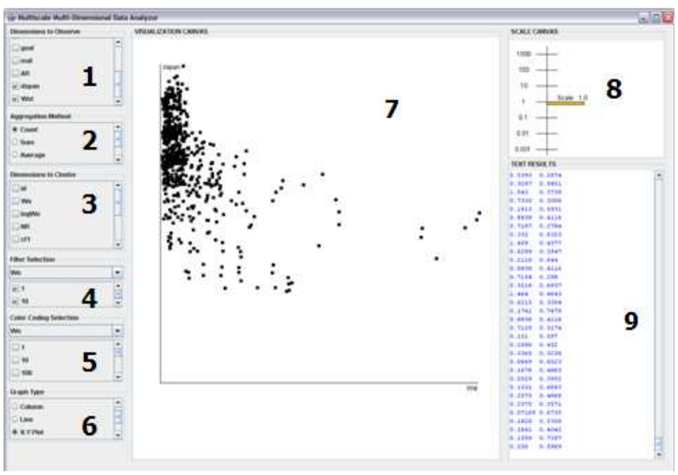


Figure 6: User interface of the prototype system

Choosing Dimensions to Observe and Aggregate: The designer can choose one or two dimensions to observe simultaneously. When two dimensions are selected, a scatter plot is generated and displayed in the primary view, as shown in Figure 6. When the designer chooses one dimension to observe and another dimension to cluster, visualization results show different clusters and their aggregated values. For example, based on the data from the aircraft wing design example, Figure 7 shows a view with Structural Weight as the dimension to observe and Gross Weight as the clustering dimension. The four boxes indicate four clusters and box size corresponds to the aggregation result of each cluster. It is easy to compare different clusters based on the box sizes.

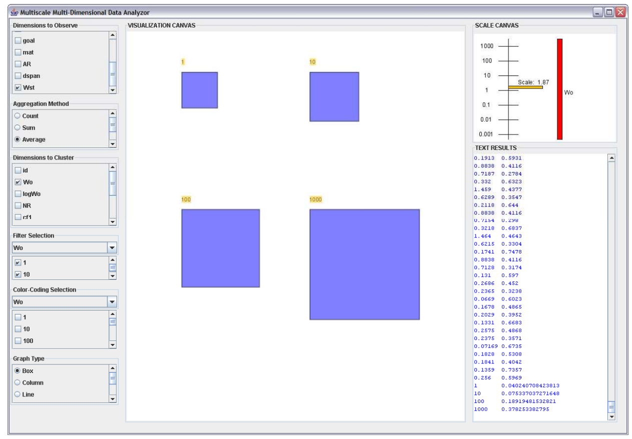


Figure 7: Example of four clusters based on different observed and clustered dimensions

Choosing Multiple Clustering Dimensions: The designer can also choose different dimensions to use to view the same data set. Different dimensions can be observed either independently or combined simultaneously. Keeping multiple dimensions independently, the designer can switch from one clustering dimension to another. Figure 8 is a view under the same aggregation method as in Figure 7, but with a different clustering dimension. As seen, different clusters are produced under different clustering dimensions.

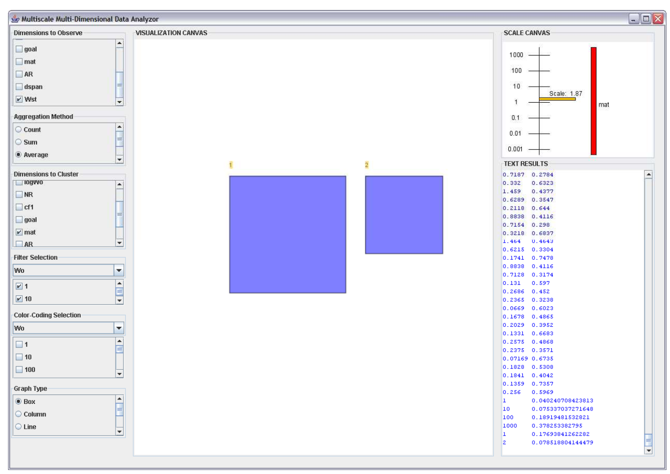
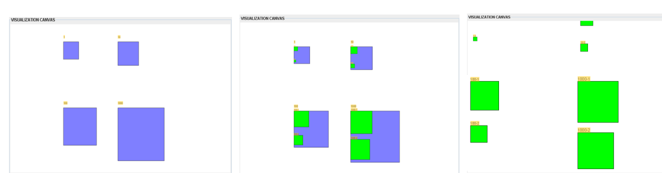


Figure 8: Different clustering dimensions

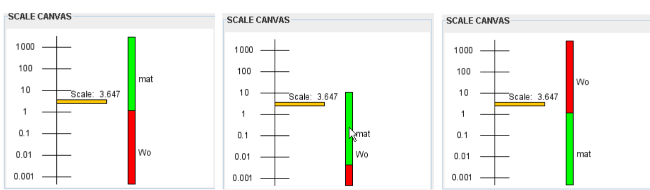


(a) **(b)** **(c)**

Figure 9: Multi-scale clustering

Combining different clustering dimensions together creates multi-scale and multi-dimensional clustering. Figure 9 shows the view results of choosing both Gross Weight and Material Type as clustering dimensions. Figure 9a is the clustering result under Gross Weight only. Zooming in, the designer sees each cluster has two sub clusters on Material Type (see Figure 9b). Zooming in further, the designer finds details inside the clusters. The nesting boxes show the relationship between these two clustering dimensions. The transition from Figures 9a to 9c is continuous and smooth through semantic zooming [51, 52].

Control Multiple Clustering Dimensions: The designer can manipulate the ordering of the dimensions for clustering when multiple clustering dimensions are involved (e.g., Material Type clusters within Gross Weight clusters or vice versa). Controlling the ordering allows exploring data from various aspects. The ordering of clustering dimensions is achieved in the scale canvas through direct manipulation. Each clustering dimension is represented as a color bar in the canvas (see Figure 10). These bars are stacked together and can be dragged and dropped. Figure 10 shows the process to adjust the two clustering dimensions in the example of Figure 9. Consequently, the nesting relationship between clusters in these two dimensions is reversed.



(a): Initial order (b):Adjusting order (c): Final order

Figure 10: Recording clustering dimensions.

4.3. Implementation

The prototype is implemented with Java and the Piccolo toolkits [60]. It has three layers. The bottom layer processes raw data and converts the data from other formats (e.g., tab or comma-delimited raw data) into a MySQL database. The middle layer is a module to connect the user interface with the database. The responsibilities of this layer include formulating SQL queries based on user preferences (e.g., data dimension, aggregation method, and filtering method), sending queries to the database, receiving query results, and constructing data tables. Finally, the top layer includes a user interaction module and a visualization module. The interaction module takes and processes the user's inputs and sends information to the middle layer or the visualization module. The visualization module presents graphs based on data tables from the middle layer and user preferences.

5. CASE STUDY: MORPHING WING DESIGN

To demonstrate the use of the iMSNCA framework in a realistic design scenario, consider the design of morphing wings for aircraft. Recently, there has been military and commercial interest in designing a wing that can "morph" from one configuration to another to improve aircraft performance during each phase of its mission [61]. A potential drawback of such a morphing wing is the added weight due to the actuators and structural supports that it would require. This requires tradeoffs during their design, namely, maximizing the change in wing shape while minimizing the added structural weight. The case study presented here involves a morphing wing that can achieve large changes in span and is modelled using a structure that consists of six design variables [62].

5.1. Data

For this study, we varied the following six input (design) variables to generate 716 different design alternatives (note: several input combinations are not feasible designs):

(1) Gross Weight (Wo): 4 levels (1, 10, 100, 1000)
(2) Cell Material (Mat): 2 levels (Mat 1 or Mat 2)
(3) Number of rows (NR): 4 levels (2, 4, 8, 10)
(4) Aspect Ratio (AR): 3 levels (2, 3.5, 5)
(5) Cell Fraction (Cf): 3 levels (0.5, 0.75, 0.9)
(6) Goal Weight (Goal): 3 levels (0.65, 0.75, 0.85)

For each design alternative, we record the predicted Change in Span (dSpan) and Structural Weight (Wst). The objective is to find the best design that maximizes dSpan while minimizing Wst, i.e., the design that offers the best compromise between these two competing objectives. While this type of problem is traditionally solved using multi-objective optimization techniques [62], our intent is to employ the iMSNCA framework to identify trends and discover new knowledge about this complex structure that would otherwise be missed if relying solely on optimization. Given the uniqueness of the structure, these insights are more useful and important at this conceptual stage of design than is finding the "best" design, which will certainly change as we learn more about the capabilities of such a morphing wing.

5.2. Results

Our prototype system offers a designer the following tools to explore design alternatives:

- Selecting different data dimensions to observe and aggregate: the designer can choose one or two dimensions to observe simultaneously;
- Choosing multiple data dimensions for data clustering: the designer can choose different data dimensions, either independently or combined simultaneously, in design evaluation;
- Manipulating the order of clustering dimensions: the designer can control how data should be clustered; and
- Changing the granularity of data clusters to examine data characteristics of data clusters.

Figure 11 shows a 2D scatter plot of the output – Wst on the x-axis and dSpan on the y-axis – of all 716 design alternatives. At this point, we have not clustered any design variables, as we are interested in the general trends in the data.

To identify which design variables, or combinations thereof, yield the best compromise between Wst and dSpan (i.e., what are good values or ranges for Wo, Mat, AR, and NR that give low Wst and high dSpan values and are insensitive to changes in Cf and Goal), we cluster the data on Wo (see Figure 12) and notice that lower values of Wo tend to yield lower values of Wst.

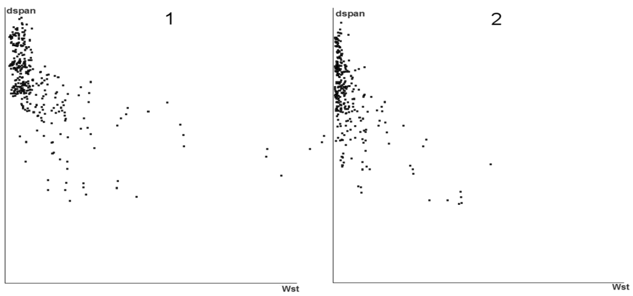


Figure 11: Scatter plots within two different clusters.

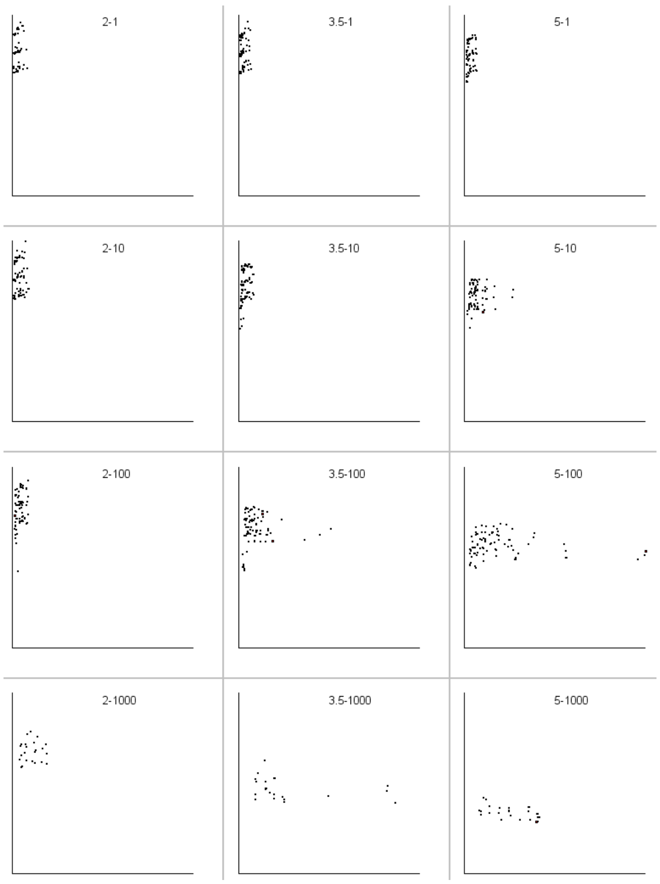


Figure 12: Plot matrix under two clustering dimensions

Clustering the data based on another dimension, cell material (Mat), produces new knowledge (see Figure 11). The Mat 2 option provides noticeably lower Wst as seen by the points residing close to the y-axis. For Mat 1, there are "gaps" along the y-axis for very low values of Wst, indicating the Mat2 option is probably a better choice.

To examine multiple variables at once to identify interesting correlations within the data, we choose two clustering dimensions. As shown in Figure 12 clustering on Wo and aspect ratio (AR) shows that for the two low Wo cases (the first and second columns), AR has little effect, while for the two high Wo cases (the third and fourth columns), the selection of AR is critical: lower values of AR are much more preferred since they yield higher dSpan values for lower Wst. The worst case would be high Wo and high AR at the lower-right corner, which leads to high Wst and low dSpan – the complete opposite of our desired design. We have thus learned that we want to avoid this region in the future.

Based on these trends and observations, we construct a final plot to "zoom in" on promising design alternatives. Figure 13 shows alternatives that have Mat 2 option and Wo = 100 (in blue) and Wo = 1000 (in red), where the data is clustered based on NR and AR. In the figure, AR increases from left to right, and NR increases from top to bottom. We can see from this plot that if we want low Wst values, then lower NR values are more desired and that lower AR values tend to yield higher values of dSpan, which is also what we want. We also notice that as AR increases, higher NR values tend to yield lower Wst values, which is an interesting interaction that we would have otherwise missed. So depending on how the problem presents itself to the designers (e.g., starting with a target Wo, determine the best wing, or conversely, given a target AR, determine how much it can morph and the size of plan (Wo) that it can support), we would use this information to help pick the best design. In either case, we know that Mat 2 is a better option for the range of Cf and Goal values examined, and that NR and AR are highly correlated at the upper end of their respective ranges, which poses unique opportunities for resolving this tradeoff while also creating the potential to yield a poor wing design as well.

6. DISCUSSION & CLOSING REMARKS

The case study results are encouraging. It shows that designers can benefit from the proposed framework, particularly the multi-scale nested clustering and aggregation approach when visualizing real design data. Our tools allow designers to compare different design alternatives from different dimensions and at different scales and to identify how individual design variables may affect design outcome and how they may be correlated. Designers can identify some "best" designs from a given data set and the corresponding value regions of design variables. The tool also helps identify regions that lead to bad (i.e., non-competitive) designs.

The contributions of our multi-scale nested clustering and aggregation framework include the following. First, it enables a multidisciplinary approach to support engineering design. This approach considers a designer's diverse tasks in manipulating and understanding complicated data and uses visualization tools to present the characteristics of data clusters that are critical to design. We believe that when the interactions among designers, design data, and design support systems become more and more important, as seen in trade space exploration, a good design support system must should integrate human factors (e.g., design tasks) and information factors (e.g., data dimensions or data values). Second, our framework outlines a practical method in analyzing multi-dimensional data visually and provides formalized definitions of this method. These definitions can guide the design and implementation of visualization tools in dealing with multi-dimensional data in engineering design. Third, the user tasks that we discussed in our framework may shed some light on visual analytics tasks in designer-driven engineering design methods, such as trade space exploration. Visual analytics becomes increasingly important to tasks like engineering design that deal with large data sets. However, many challenges still exist in developing general visual analytics tools, including identifying basic analytical tasks and reducing the complexity of information displayed on workspace [63]. Our multi-scale nested clustering and aggregating approach will not only enrich the repertoire of analytical tasks but also help to control the amount of information to visualize.

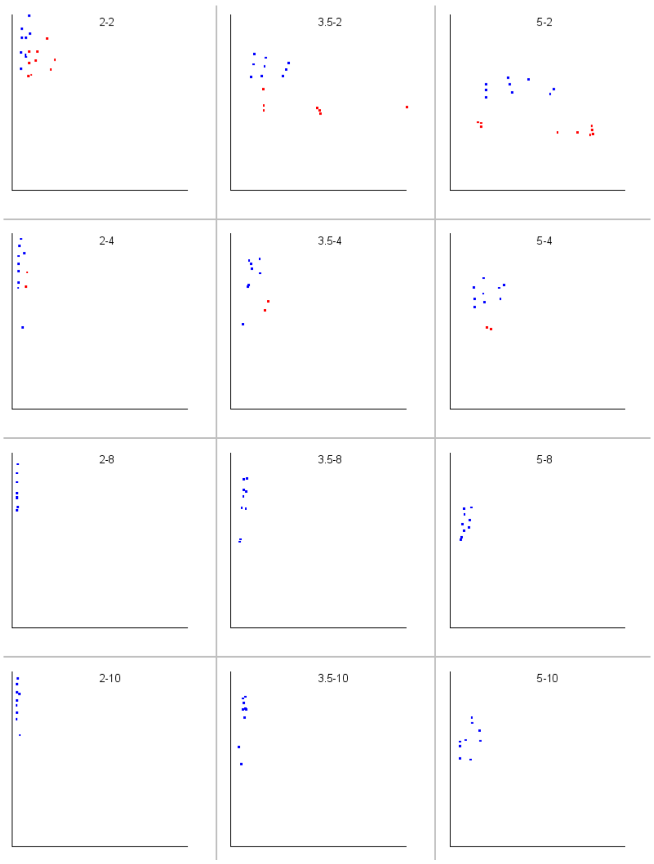


Figure 13: Three-dimensional clustering: clusters on the third dimension are color-coded

Some limitations exist in this research. For the theoretical framework, the identified tasks are incomplete as they are based largely on our empirical observation of engineering design. To improve and validate the framework, we need to consider diverse users and their tasks. On the aspect of system design and implementation, our prototype can also be enhanced in many ways. For example, we need better tools for selecting the dimensions of interest. Currently, users need to specify these dimensions one by one using checkboxes. For large data sets with hundreds, or even thousands, of dimensions, going through all dimensions to identify interesting ones is a daunting task for users.

Future research efforts will proceed in several directions. First, we will refine our framework by investigating what other interaction tasks should be included, such as cluster-size manipulation. Second, we will explore the integration of advanced statistics methods on data clustering and dimension-reduction, as discussed in [44, 45] into our iMSNCA framework to offer designers more comprehensive data analysis tools. Furthermore, we plan to validate our framework and system with industry data (e.g., corporate marketing data) and research data (e.g., physiology data) by soliciting data from engineering designers and making our prototype system public for downloading.

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