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An Analysis of the Effectiveness of a Multi-Disciplinary Decision Support System on System-Level Decision Making

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ABSTRACT

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Decisions Support Systems (DSSs) are used to enhance decision maker speed and effectiveness. However, without a view of an entire system, any decision may have unanticipated effects such as sub-optimal outcomes. The purpose of this research is to show that with a system-level analysis, more informed decisions can be made that take into account a larger system or greater number of dimensions or objectives. This research also explores the benefits of using a DSS over analysis of unprocessed data and the effectiveness of integrating a product design generator (PDG) with a business DSS, creating a system DSS, where system-level effects can be analyzed. These are connected using software which allows them to be interactive, and dynamically updating. After this DSS was developed a variation was also made and decision makers evaluated these tools to identify how they performed in comparison to each other. In one variation, aspects of the tool were split up, guiding the decision maker through the analysis while the other did not. Using survey questions and recording decision makers' actions, it was found that decision makers are significantly faster and came to better conclusions when using the DSS over unprocessed data. However, it was also seen that the difference between the two variants of the System DSS tests was insignificant. This suggests that the limits in potential interactions in the one variant of a system DSS did not substantially reduce the ability of a decision maker to explore and make good design decisions. Overall this research showed that having a system-level tool is better than the unprocessed data, and that more extreme differences in a DSS are required for improved comparisons to establish which visualizations and elements are most effective in a System DSS. Future effort should be made to completely isolate different portions of the System DSS and see how well users are able to make decisions with it compared to the full system analysis.

Keywords: decision support system, product design generator, System DSS, multi-disciplinary decision making, engineering systems

ACKNOWLEDGMENTS

First I want to say thank you to my parents and siblings for supporting me and believing in me, they always told me I was the smartest one in the family, I'm not sure I believe them, but it's nice of them to say anyway! Next I want to thank my advisor John Salmon for accepting me into the BYU Engineering and Systems Design (BESD) program and allowing me to work on something that I truly found rewarding and enjoyable. When I graduated with my Bachelors degree I had the desire to work on systems analysis and systems efficiency, and I am grateful for the opportunity I had to do just that. Third I would like to thank Miriam Busch for passing my name on after I had come in to bother people about admissions (unsuccessfully might I add) multiple times, without her I never would have had the chance to talk to Dr. Salmon and consequently would not have been able to attend BYU. Last of all I want to thank my Heavenly Father for giving me the strength do to the things that I never could have done on my own.

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CHAPTER 1. INTRODUCTION

Decision Support Systems (DSSs) are widely used in industry today. DSSs are software tools made for the purpose of assisting individuals in making decisions by giving them the ability to analyze data rapidly [4, 5]. The use of DSSs helps decision makers improve their decisions in terms of both speed and accuracy [6, 7].

The lack of a system view can hinder the decision maker from choosing an optimal solution for the system [8, 9]. A common mistake can result from focusing on and optimizing a specific sub-system or a portion of the design space, at the expense of a global optimum across the entire system. Paradoxically, if every individual sub-system is optimized for efficiency, effectiveness, etc., there is no guarantee that the total system would be optimized, in many cases it would be impossible to optimize all sub-systems due to differing design objectives [10].

In the following research, a DSS was developed for the purpose of testing if a system view can help the decision maker beyond the non-System DSS. The System DSS consists of an integrated product design generator (PDG) and business DSS. The integration of the two show interactions in the system that may not have been considered if the two were not connected and gives a better view of the system that is being affected. Using this DSS, experiments were performed to show whether or not it was effective in increasing decision making capability. It is hypothesized that the System DSS is a better method than unprocessed data or a constrained DSS (i.e. limiting views on interactions) as the former shows more trends and relationships on interactions between systems.

1.1 Problem Statement

DSSs have been developed and are used to help with analysis, however, even with the use of DSSs, data analysis can have many problems [11]. Some challenges regarding the data include: inaccurate data [12], delayed data [13, 14], excessive data [15], and unorganized data [16]. In addition, a continuing problem in industry is making effective decisions that take into consideration system-wide effects [17]. Therefore, the combination of inadequate data analysis coupled with a limited view of system-wide effects can result in poor decisions and designs. Without proper understanding of these challenges, many DSSs are underutilized and potentially ill-constructed [18]. Furthermore, as systems get larger and communication become faster, individuals struggle to understand how to interpret the exponentially increasing amount of information [19]. Large amounts of poorly presented data can cause decision makers to make worse decisions than if they were presented with less, but focused data, because of the inherent limitations on their ability to interpret all of the data simultaneously [20]. In other words, the decision makers perspective of the system is limited as the system grows, which further hinders their ability to make good system-level decisions.

Having poor or limited systems analysis can cause problems in engineering and business [21]. An example from the automobile industry illustrates the lack of system communication, analysis, and integration. An automobile company in Detroit decided to analyze an imported car from Japan to better understand why the Japanese parts had better precision and reliability at lower cost than the American cars. In their analysis, among other things, they found that the Japanese company had used the same bolt three times to mount the engine, whereas the US company had used three different bolts for their assembly. The company in Japan did not need the additional wrenches and bolt inventories, which were used by the company in Detroit, and as a result assembly was faster and cheaper for the company in Japan. In the US there were three teams of engineers, each responsible for their bolt and mounting process. Although, in their limited perspective, they each achieved the requirement of mounting the engine, each team used a different type of bolt. In contrast, there was one designer in charge of engine mounting for the entire company in Japan [17]. The three teams in Detroit did not have a system-wide view of their configuration, while the designer in Japan did, and because of this was able to make a better system-level decision [22].

Another example of this is found in older manufacturing practices where each discipline seeks to find an optimal solution for their own objective, resulting in the system never reaching the global optimum [23]. The general practice was to build "quantities of scale" to decrease the cost for each part manufactured. This became an effective way to increase efficiency inside a single process. Although the efficiency for each batch is very high as it runs, without observing the effect on the system as a whole, it is hard to see that this does not reach the system's potential level of efficiency. If there is an error in a batch of processed goods, then it may not be discovered until that batch is worked on later, which could be after thousands of parts have already been made, rendering all of them defective. Also, it creates problems when customers have demand for different types of products coming through the same machine. Generally, it would take so long to switch over the machine to the other die that batch processing was the only feasible way to accomplish the goal. This strategy required the manufacturer of the part to look forward and estimate how many sales they believed would be made before the next batch was run. Furthermore, inventory costs would rise from this technique because all of the batch parts could not be processed immediately. It took an analysis of the system to realize that a "pull" system is a better method, where the parts being produced are regularly and rapidly switched. "Single piece flow" resulted from a system-level view. This process, compared to batch processing, is shown in Figure1.1. With the capacity to change over quickly to different products, smaller inventories could be made and customer demand can be followed more closely [24]. All of this knowledge of how to truly become more efficient was gained by considering the entire system rather than one section of it.

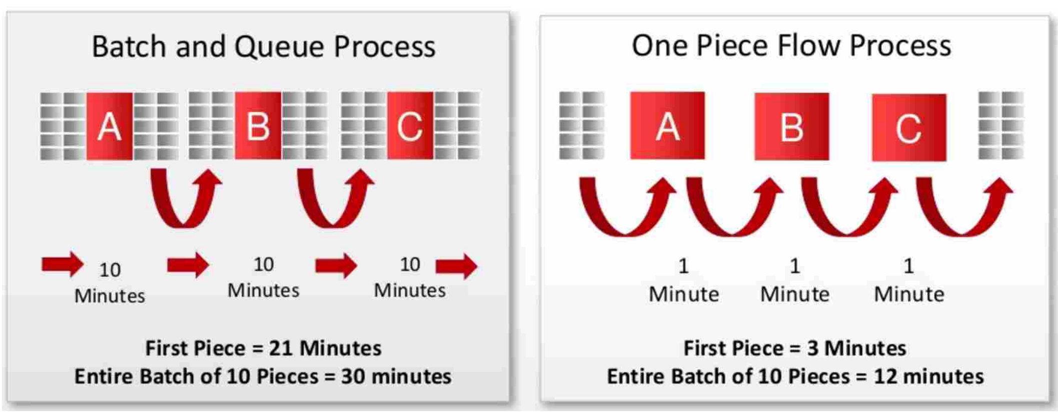


Figure 1.1: One piece flow is a better system choice than batch processing, though batch processing can seem more efficient without a system-level perspective [1]

Furthermore, in optimization problems, there are sometimes many "good" or "local" optimal points. As can be seen in Figure 1.2, there are many local minima, but only one global minimum found in the center. Many of these points may provide a feasible solution and suit the requirements of the design. However, without examining the entire surface, one may miss a much better point, which is the global optimum across all design parameters. This is analogous with systems design, when employees or engineers focus more heavily on one area and may not find the optimal global solution [10]. If a poor optimization algorithm was to start at a particular corner of the example function, it would descend into the nearest "valley" and converge onto a local minimum and deem it as the optimal point. However, without a view of the entire surface, an algorithm (and likewise the disciplinarians in multi-dimensional systems design problem) may not find the better global optimum.

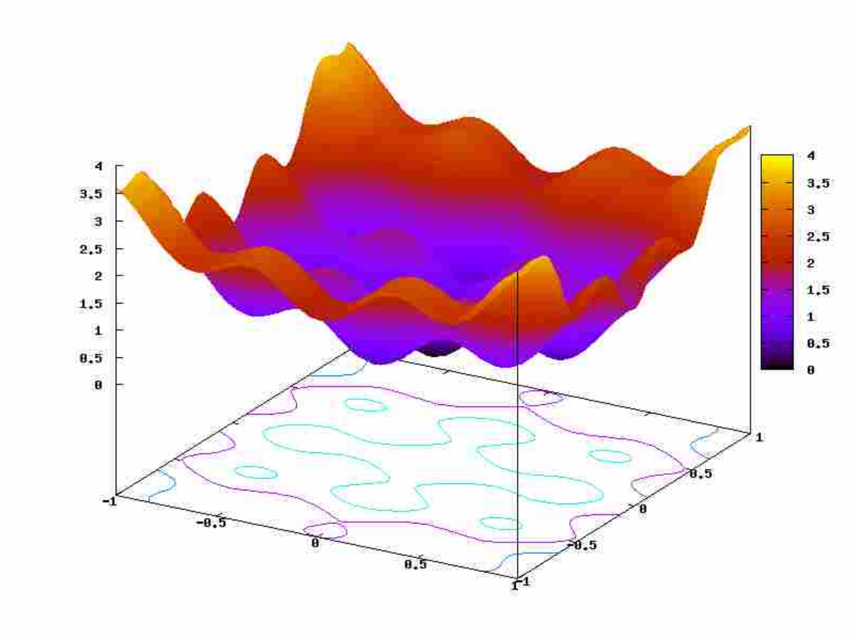


Figure 1.2: A design space with many local optima, but only one global optimum (for minimization) [2]

1.2 Background Research

Some recent studies have investigated the enabling technology from DSSs for improving data analysis in multi-objective spaces. One study explored the development of a DSS that aids in the emotional process of decision making [25]. Another study explored performing dynamic analysis on temporal (time-dependent) data to create a dynamically updating DSS [26]. Another develops a system that is able to help the decision maker with situational awareness to better understand the performance of different applications [27]. Others focus on optimization models for business planning [28]. In the realm of product development, researchers experimented with how decision makers implement new products effectively [29]. Finally, multiple articles discuss creating automated product designs through a product design generator (PDG) [30, 31]. An example of a DSS is shown in Figure 1.3. This DSS was made to help the Upper Midwest Environmental Sciences Center (UMESC) make decisions about "land acquisition, environmental review, management planning, and provide a valuable tool for communication and outreach".

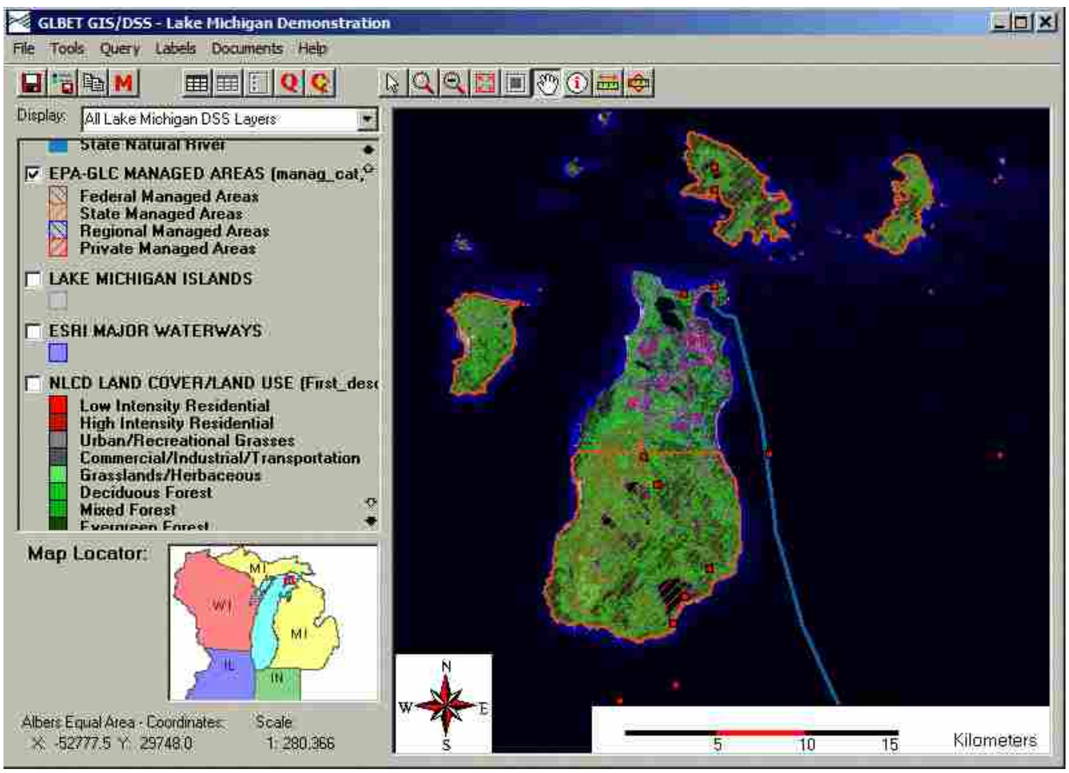


Figure 1.3: A DSS used by the UMESC

Though the use of DSSs is usually well received, the use of a system-wide DSS has not been thoroughly explored. Most would agree that a DSS is more time effective than traditional analysis with unprocessed data. However, the implementation and use of such tools is limited and in many cases not developed to account for the entirety of the system it affects.

With effective DSSs, employees at all levels can potentially make improved decisions because they have a better view of the entire system based on quantitative analysis. DSSs have become more common in the past years, especially with the advancement in computer technology [32]. Research is ongoing into how DSSs increase effectiveness and help with decision making by focusing the DSS on useful information [33]. These efforts have resulted in the development of improved systems geared toward many different industries or needs, such as ambulance dispatch or flood warnings in California [34, 35]. DSSs facilitate data fusion to support better decision making when time for additional data analysis is unavailable. One way to increase productivity is the effect of having information dynamically update because it allows user to analyze the data faster [36]. PDGs have also been developed for instantaneous product design updates [37]. With these PDGs, creating a product that is aesthetically pleasing, structurally sound, and meets design requirements can be evaluated with respect to its predicted success in the market [38]. Despite these advancements, the effectiveness of a dynamically updating, multi-disciplinary, integrated, decision support system has not been fully explored across all possible interactions.

Building upon past efforts, this research explored if interactive, dynamically updating DSSs based on engineering models helped decision makers ascertain better system-wide conclusions. In many cases, engineers do not make optimal business decisions because they cannot see how their decisions affect the business in the long run. This research aims to show that detailed systems models can help all stakeholders (i.e. engineers, analysts, management, and operators) better understand the connection between the engineering processes and economic factors as well as make faster decisions that take into account the effects of the whole system.

1.3 Research Questions and Objectives

The objective of this research is to test if an interactive, dynamically updating, multi-disciplinary, integrated, decision support system which brings multi-disciplinary data together in an organized way, assists in the decision-making process, specifically in the case where a new product is under consideration to be added to a company's current product lineup. Furthermore, two questions this research seeks to answer are 1) How much better is a DSS for decision making than using unprocessed data 2) In which ways is a view of system interactions more beneficial than a singular view of a process? The ability to view interactions between DSSs, namely an integrated product design generator and integrated business decision support system, has also not been sufficiently explored. To achieve this objective, a DSS was developed, based on business data and engineering models, and tested to evaluate its effectiveness in helping with decision making. Experiments and survey questions from decision makers were executed and answered to evaluate the DSSs measures of performance. To enable this testing, JMP [39] a dynamic graphical software was integrated with Solidworks [40], for product engineering, and Matlab [41], for business optimization, in a unified System DSS.

This research contributes to engineering design by evaluating how connecting automated design models in DSSs can help decision makers better understand multi-dimensional systems. It is hypothesized the decision makers can make better overall decisions because they have a better understanding of the interactions between the engineering models and business relationships within a company. Decision makers can see how their actions positively or negatively affect a system as the DSS generates results in near real-time and analyzes effects from any change in the inputs. A knowledge of these system-level impacts can improve the decision maker's confidence in making choices as well as help them choose more effective system solutions. If system models are adopted, engineering companies can be more competitive with better designs from better decisions that take into account interactions between engineering and business parameters.

The following are the hypotheses that the research explores:

- The DSS allows for the understanding of what trade-offs can be made between the business and product design aspects
- The DSS increases the understanding of the effect of product design on a business
- The DSS shows that a system linked analysis improves system-level decisions
- Decision makers can see how small changes affect the system
- The DSS improves the ability to make decisions
- The DSS creates a better view of engineering and business interactions than unprocessed data
- The integrated data supports reaching better decisions than unprocessed data
- More choices can be analyzed in the DSS than with the same amount of time using unprocessed data

1.4 Thesis Overview

The remainder of this thesis is organized with Chapter 2 discussing and presenting the methodology and overall approach to address the research objective and contains all the information about how the DSS was constructed, including the PDG, the business DSS, and the integration of the two systems. Chapter 3, Evaluation and Assessment, presents information on the testing plan to evaluate how decision makers use and assess the System DSS. It also discusses the difference between the two variants of the System DSS. The Results and Analysis chapter, Chapter 4, contains the results from the testing and discusses the conclusions drawn from that analysis. A conclusion chapter, Chapter 5, wraps up this research, presents limitations, and discusses potential future work.

CHAPTER 2. METHODOLOGY

2.1 Overview

A variety of DSSs could be used to address the questions posed in the previous chapter. It could be one of seemingly infinite combinations of analysis tools crafted into system-level tools further tested by comparing them to the unprocessed data with which they were developed. The methodology described here was chosen for a number of reasons. It was preferred, though not necessary, that the DSS could be used in a real setting, or to help in making a decision in a real-world problem. This was achieved by working with a company who wanted to know if adding a bariatric chair to their company's current product lineup was a good idea. This real-world problem met the criteria of what was needed to justify integrating a PDG and Business DSS into a System DSS. The System DSS would be able to answer the question of what needed to be done to the current business to increase profitability as well as what effects introducing this specific product would have on the overall business given the chosen product design parameters. To make this multi-objective system function, a DSS was constructed by creating an optimizer for the business inputs. After this was done a product design generator was developed to help parametrically design the bariatric chair. After the development of these two sections, they were integrated into one System DSS inside JMP, where both systems could be analyzed. This section discusses in detail the development of the PDG as well as the business DSS.

2.2 Approach

A number of requirements were established to develop a functional DSS for analysis. Most importantly, the DSS includes all necessary information for the decision maker to make a system-level decision. The DSS supports decisions about thr new engineering product line in which the product can be designed from the ground up. It is parametrically developed with design parameters for the various key dimensions. The input parameters are rendered in a CAD system for visual analysis of the tool. The product's structural integrity is also analyzed with the PDG. The business data is analyzed to establish relationships between the number of product lines, advertising expenses, raw materials cost, and their effects on the overall profitability of the company. The parametric engineering model is connected to the business data and effects are shown on the interaction between the two. For example, if the decision maker changes the wall thickness of the product, the DSS illustrates the decisions impact on the overall profitability of the company. In another decision, if new product lines are added, it displays how the total revenue is affected. Integrating this information, decision makers are able to make better informed system-level decisions from a variety of perspectives, including technical and non-technical views.

The product design generator parametrically modifies a bariatric shower chair similar to the one shown in Figure 2.1. Although, shower chairs are a common item on the market, shower chairs with weight capacities of over 500 pounds are not commonly available. Using the parametric design tool, a person can easily create a chair which has the ability to support weights of well over 500 pounds. With the product design generator there are many combinations for the design of the chair and an optimal solution can be found.

The business DSS is tailored to a company that works in making bariatric bathroom products. The product lines and sales are modeled after the real data from the company. The inputs include elements such as advertising spent, product lines per product family, and advertising distribution per product family. Using these parameters, items such as overall profit, number of employees, and various expenses can be readily calculated. Integrating the business data with the product design generator shows more effectively how the designer can make a system conscious decision.

Processing the data facilitates understanding as decision makers interact with the System DSS to see how changing input parameters effect other aspects of the system. A high-level, concept map, displayed in Figure 2.2, shows the linkage between the engineering and business modules. The elements from the PDG are outlined on the left in dashed purple and the Business DSS is outlined on the right in dashed pink. The input parameters to each of the various modules are shown in red boxes, with the analysis programs in orange, the System DSS module in green, and the final output information in blue. Each of the inputs are sent to their respective analysis program, then from those two modules information is passed into the System DSS. The System DSS then

Figure 2.1: A real shower chair similar to the one that can be designed in the PDG. This chair design has a maximum weight capacity of 350lbs [3]

provides the output values. This process enables the decision maker to iterate quickly on all input parameters, explore the effects across the system, and identify optimal solutions. In summary, the following tasks were completed to meet the research objective:

- Develop a dynamically updating product design tool (PDG) based on engineering models and analysis (CAD, structural analysis, and product visualization).
- Develop a dynamically updating business DSS to display impacts from business operation inputs.
- Integrate the PDG and business DSS into the system-level DSS.
- Analyze the effectiveness of the system-level DSS by measuring speed and accuracy of decisions and collect evaluations from test subjects on DSS usefulness and performance.

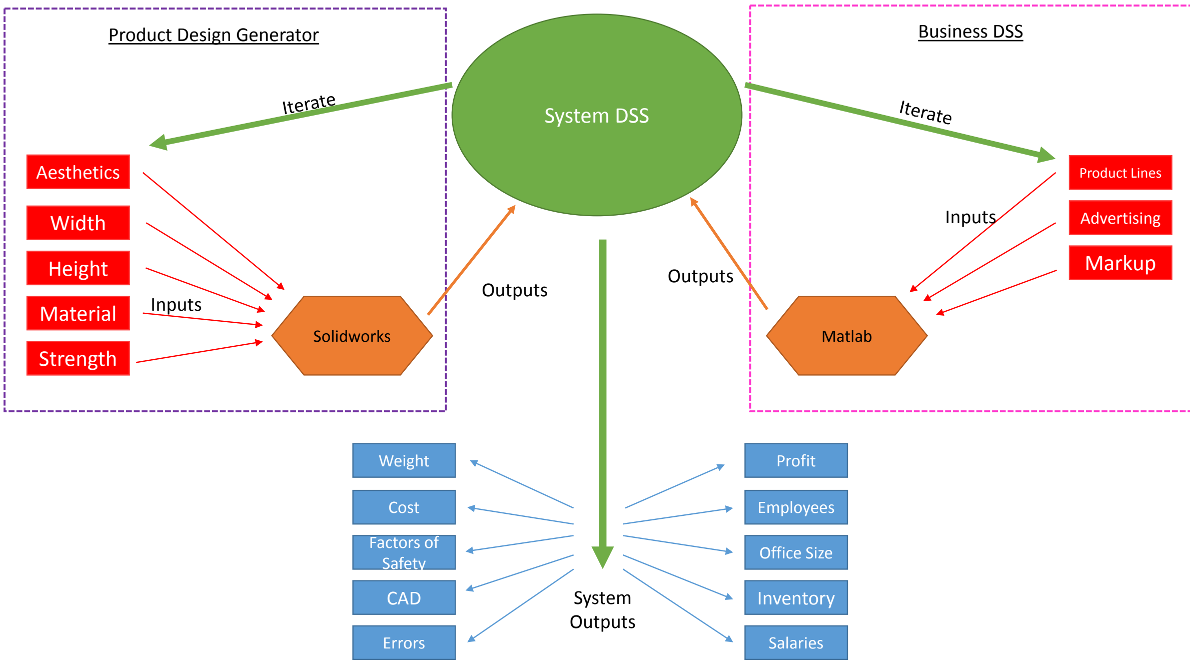


Figure 2.2: Conceptual diagram of the System DSS with the PDG on the left and business DSS on right

2.3 Product Design Generator

The product design generator (PDG) is used to assist in the product design process with the capability of generating thousands of potential designs in near real-time [37,42]. The PDG accepts user-defined inputs and updates the product and all of its specifications dynamically. As mentioned above, a parametrically designed bariatric shower chair was selected to support the current decision faced by the sponsoring company's decision makers.

2.3.1 PDG Model Development and Formulation

The PDG uses many different calculations and assumptions to generate designs and specifications. One key calculation is an estimate of a maximum load F_l in normal conditions on the bariatric shower chair. This is calculated by using equations 2.1 and 2.2 where the acceleration found in the first equation is substituted into the second equation:

$$V^2 = V_0^2 - 2a\Delta y \tag{2.1}$$

$$F_l = ma + m(\frac{V_0^2}{2\Delta y}) \tag{2.2}$$

where V is the final velocity (set to 0), V_0 is the initial sit velocity (assumed to be 3ft/s), a is acceleration, Δy is the slowing distance (assumed to be .25ft), and m is the mass of the user. This equation is then split across the four legs, and the worst case scenario occurs when the user of the chair sits with most of their weight onto one leg. This worst case assumes that the user applies 77% to one leg, with 90% of their weight onto the back portion and 85% of that weight on one of the sides. The factors of safety for buckling in the legs were calculated using the buckling equation:

$$F_b = \frac{\pi EI}{(KL)^2} \tag{2.3}$$

where F is the maximum critical force, E is the modulus of elasticity, I is the area moment of inertia, l is the length of the column, and K is the effective column length factor (which is 2 in this case). The maximum critical force was then divided by the worst case force F_l to calculate the factor of safety FoS_b shown in equation 2.4. All factors of safety under two were considered unacceptable to the design and would add penalties to the final profitability if selected.

$$FoS_b = \frac{F_b}{F_l} \tag{2.4}$$

The factors of safety for stress in the width and depth of the seat base, strength of the back post, and bending in the back were also calculated. The stress in the seat base was calculated in the x and z directions with y pointing in the vertical direction. Boundary conditions were created such that points are fixed at the position of the legs with the weight placed at the center of the seat base. This was the case for the x and z analysis. Bending in the back of the seat was calculated assuming fixed points at the left and right edges where the supports are located. Lastly, a bending calculation was made on the seat support posts, where the weight was focused onto the top middle of the seat back and the supports were fixed to the top of the seat base.

The maximum stress σ_m on the material was calculated using the stress equation:

$$\sigma_m = \frac{Mc}{I} \tag{2.5}$$

where M is the bending moment, c is the distance to the neutral axis from the edge of the material, and I is the second moment of inertia. The factor of safety FoS_s was calculated using equation 2.6 where the yield stress σ_y was that of PVC (5000 PSI [43]) and it was divided by the maximum stress σ_m from above.

$$FoS_s = \frac{\sigma_y}{\sigma_m} \tag{2.6}$$

The chair model was updated by a connection to Solidworks. This was done by sending the 10 chair parameters (shown in Figure 2.3) to Solidworks, reevaluating the CAD model, and passing back the new information including the picture and volume information. Using this tool multiple parametric designs could be generated when changing design variables, with examples of chairs from changing two parameters shown in Figure 2.4. In these examples the seat thickness is changed on the y-axis and the back height is changed on the x-axis.

However, since it required about twenty seconds per run to render each of these chairs, the objective for a real-time analysis capability was not reached. To enable near real-time analysis, 1500 designs were created using a Latin hypercube to uniformly explore the design space. Pictures and values were saved for each design setting. A nearest neighbors algorithm was then implemented in the System DSS to enable the comparison of the current chair parameters to the closest parameters of a saved design and then load the saved picture of that design in near real-time. The code for the connection to Solidworks is shown in the URL contained in Appendix A.1

Without running the Solidworks model every time, the volume could not be adequately calculated. Therefore, a separate method was needed to calculate that output. Although using a nearest neighbors algorithm on the 1500 chair designs provided the associated volumes, which could be used to interpolate different design volumes, a neural network was used to provide greater accuracy. Using the same 1500 runs a neural network was run which created an equation that could predict the volume of the chair for any input configuration. Once this neural net equation was integrated with the DSS, the full PDG could run in near real-time. The equation general from the neural network is shown in the URL in Appendix A.2.

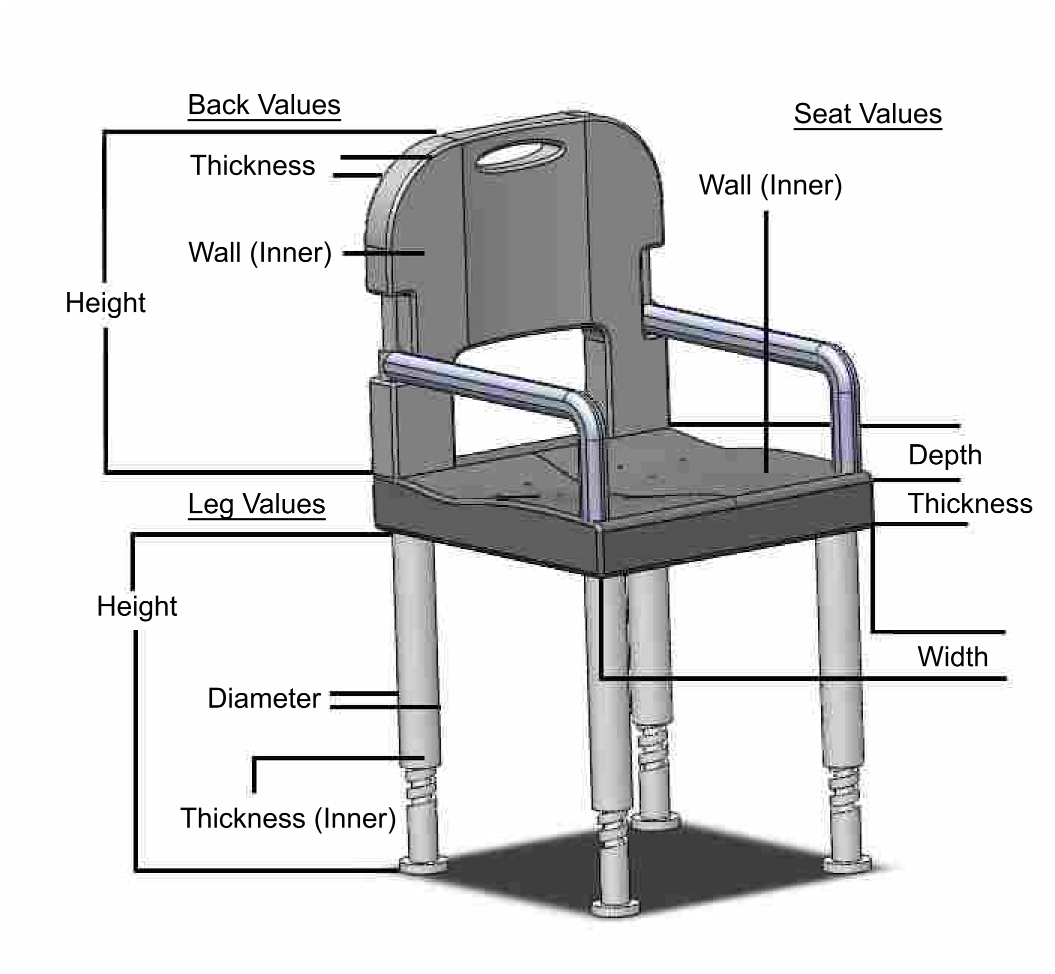


Figure 2.3: The adjustable parameters of the chair are shown in their respective places

Finally, the unit cost was calculated by the amount of material used in the chair and an estimated added manufacturing cost. The investment cost was estimated from similar products that the company had designed previously.

2.3.2 PDG Description and Operation

The product design generator has multiple inputs as shown in Figure 2.5 such as chair load, leg height, leg diameter, leg wall thickness, seat width, seat depth, seat thickness, seat wall thickness, back height, back thickness, and back wall thickness. Using mouse actions the decision maker is able to adjust any of these values through the control element accordingly. As the various sliders update, the picture and output parameters also change. Using these sliders, the decision

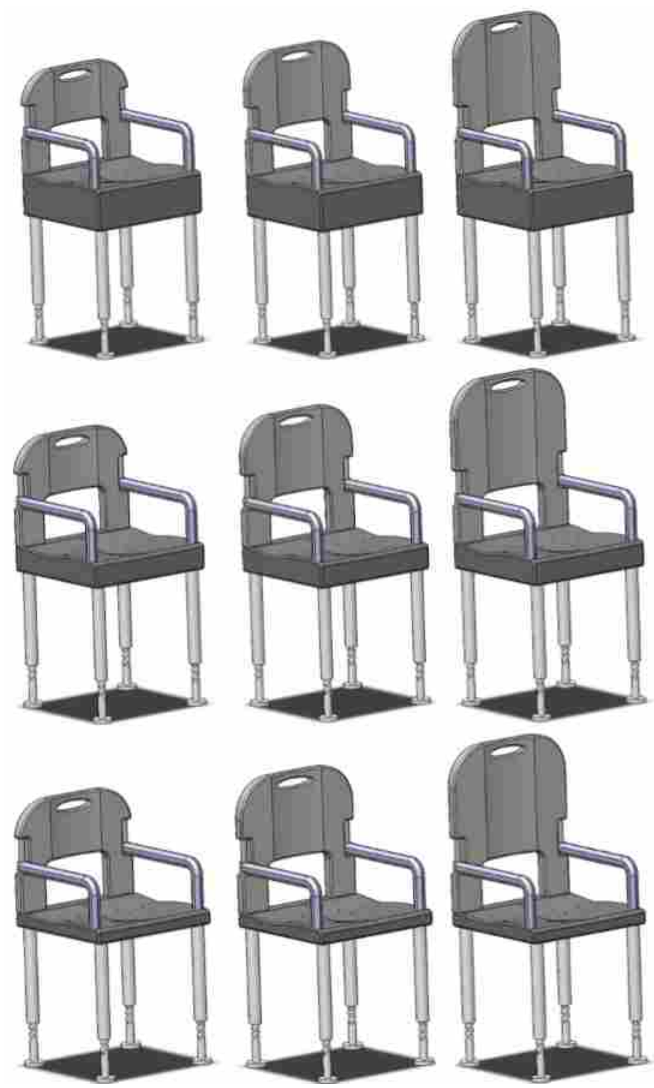


Figure 2.4: Bariatric chairs that can be parametrically designed through Solidworks changing 1) the seat thickness (varied in the y-axis) and 2) the back height (varied in the x-axis)

maker can quickly find a chair that is suitable based on desired objectives and preferences for the company. In addition to adjusting parameters, the decision maker can generate both random models as well as create an exact model of the design in SolidWorks by clicking the “Create Exact CAD” button just below the sliders on the input section of the PDG. The right hand side of the PDG displays a number of output design values, including the factors of safety for the legs buckling, back bending, posts bending, and seat bending in width and depth (see Figure 2.6).

Other outputs of the PDG include weight, appearance, unit cost, potential design errors, and investment cost to build the chair. Using all of these outputs the decision maker can decide on

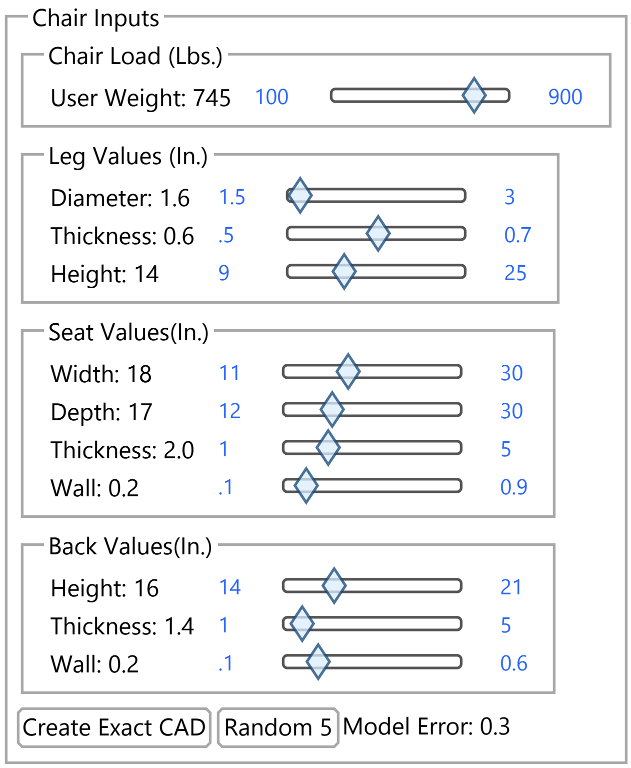


Figure 2.5: A detailed view of the input design parameters for the PDG

a design that is suitable for the needs of the customer while focusing on minimizing costs for the company. Also, if they want the chair to be extra robust in certain areas, they can easily make this change. The point of this kind of interactivity is to enable a decision maker to select exactly what they want and understand what the parameters they change are affecting.

The decision maker also has the ability to save their designs into one of the five save slots, entering the save number they want to use, and then pressing "Save Product Values." They could then recall that saved chair by clicking the respective number in the five save slots.

As input parameters are changed an image of the product can also be viewed inside the PDG. This image updates according to how close it is to one of the 1500 designs that are pre-processed. A few of these designs are shown in Figure 2.7.

Once these sections are combined the PDG is complete with a screenshot shown in Figure 2.8.

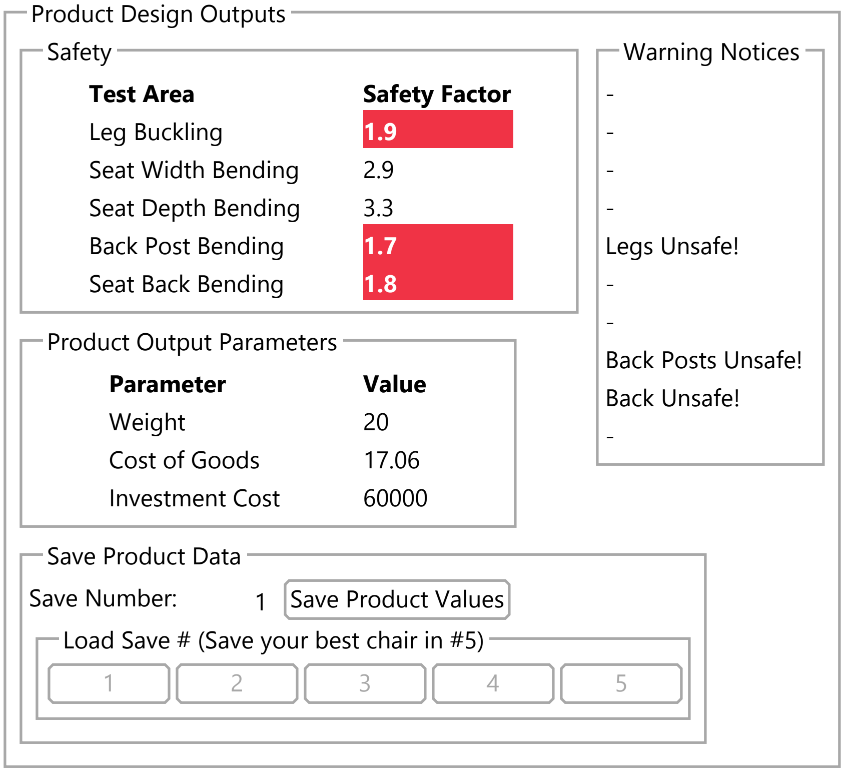


Figure 2.6: A detailed view of the output design parameters for the PDG

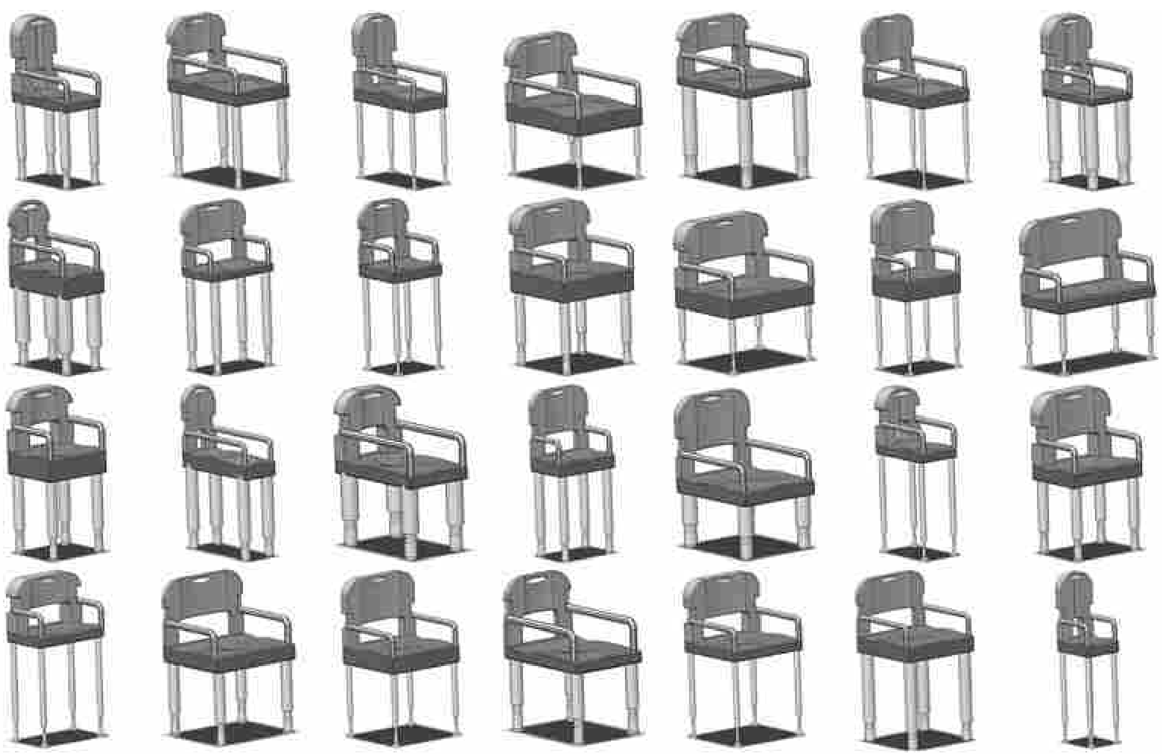


Figure 2.7: 28 possible designs among the 1500 different chairs pre-processed by the PDG

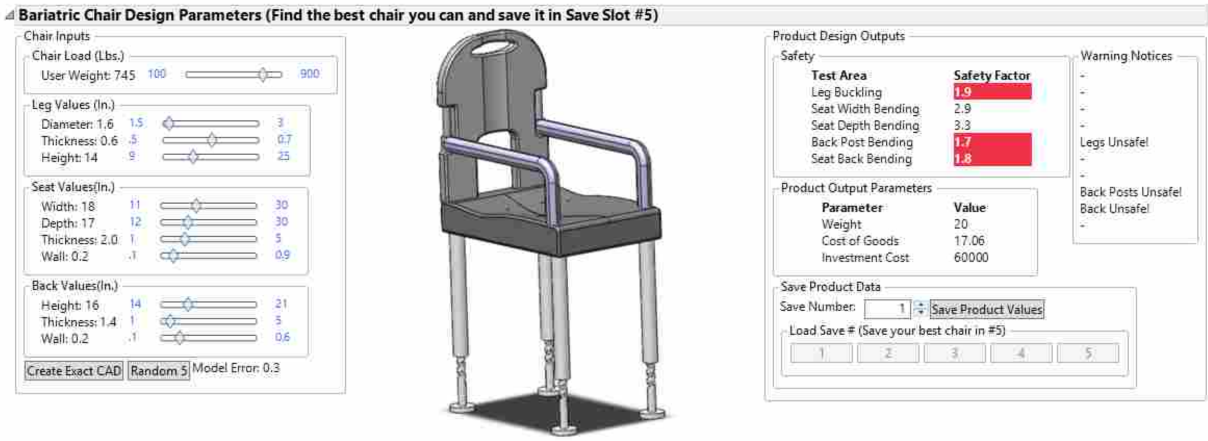


Figure 2.8: The PDG portion of the System DSS

2.4 Business Decision Support System

Optimization is a growing field with increasing areas of application. One of these areas has been to optimize and improve business performance [44–46]. Due to the complex nature of a business, the actual application of various optimization methods is difficult and generally involves data mining and the hiring of analysts to break the business down into manageable and related components [47, 48]. The costs of such tools can be prohibitively expensive for small, start-up companies [49]. In order for these companies to remain competitive and have an opportunity to survive in such a market, simplified optimization methods with readily available information and tools need to be developed. Silva et al. provided one such example of how optimization can be used to find effective business parameters [50].

An analysis on a small business [51] was performed using income and expenditure data from 2006-2014 to identify critical parameters and relationships that influence the overall profitability of the company. Optimizing these critical parameters, a business can make more profitable choices specifically in areas of product development and investment [52].

2.4.1 Parameter Relationships

A business is a complicated conglomerate of many different facets of income and expenditures [16].The methodology for setting up the small business model involved mapping out the inputs and outputs of the business to determine how these facets relate in a company. The model also involved determining the constraints of the business which could reflect the long-term financial or growth goals of the company as well as any resource limitations.

The inputs of the business have been defined to include those aspects of the company that are determined or controlled by those operating the company. In this case, the inputs included:

- Number of employees
- Employee Salaries
- Floor size of working location
- Advertising investment
- Product lines being sold in the various product families
- Product sales markup
- Inventory retained
- Advertising split among product families

Each of these inputs are dependent on each other to some extent. The top level variables which would be changeable by the user inside the DSS were chosen by observing which dependencies existed among all the variables and which would be able to update without inputs beyond what had already been given. The top level inputs include the total money spent on advertising, the markup per product family, the advertising percentage for each product family, and the number of product lines per product family. The products were separated into four different families for analysis on product types rather than individual product lines because each product family performed differently in terms of sales revenue. This created a total of thirteen input variables.

The outputs of the business have been defined to be those things which occur as a result of the business operation inputs but are not directly controlled by the business. The main outputs include the quantity of each product sold and the overall profit of the company. All equations and values used in this model were in terms of a annual summations, e.g. the annual quantity sold, annual salary, or annual advertising cost.

2.4.2 Business Model Formulation

Profit is sensitive to all of the chosen design variables. It was found that advertising, product lines, and markup are all connected to the number of sales. As advertising increases, sales also increase. With too much spent on advertising, however, the return on investment from that advertising drops. The relationship profit has with advertising is best described by the law of diminishing returns [53]. Marking up the product also affected the quantity of sales. With an excessive markup, no one buys the product; with too little of a markup, the business is not profitable.

JMP® statistical software was used [39] to determine the relationships between the many mentioned parameters provided by the sponsoring company. The equations relating the various parameters were determined using fit models of actual past data discretized by year. The equations determined using JMP® for use in the optimizer include the markup multiplier per product family and the quantity of products sold per product family.

The markup multiplier equation per product family K_i was obtained using data of the quantity sold of the product family versus markup at that quantity sold M_i. The regression equation for this data followed a reciprocal trend meaning that as the markup increased the quantity sold decreased. Five of these equations were needed, one for each of the five product families. An example of one of these equations is shown in equation 2.7. All other examples are values used for the bariatric chair equations which were derived from scaling one of the the other product lines.

$$K_i = \frac{(-200+2000) * \frac{1}{M_i}}{50} \tag{2.7}$$

The quantity of products sold per product family Q_i was developed using a 2-dimensional linear surrogate model which is a function of advertising expense per product family A_i and number of product lines per family L_i. Markup ratio was considered to be added into the surrogate but was not included due to its low correlation according to step-wise regression. It was later added more appropriately as a normalized scaling factor. Equation 2.8 shows a formula generated by the regression process.

$$Q_i = 5*(K_i*((-50)+0.0004065*A_i+200*L_i+((L_i)-.1125)*((A_i-200)*0.00039193))/10) \tag{2.8}$$

Other equations used but determined through means other than JMP include revenue per line, total revenue, product investment cost, total product investment cost, total number of sales, number of employees, inventory, office size, office cost, total salary cost.

Revenue from one line R_i was calculated by multiplying the projected quantity of sales by the production cost P_c and the markup ratio as shown in equation 2.9. The production cost for the chair in this instance is passed in by the PDG. In other lines it is already determined by the current cost for the company to make that product.

$$R_i = Q_i * P_c * M_i \tag{2.9}$$

The total revenue R_t for the company was calculated by adding all the revenue from the individual lines as shown in equation 2.10.

$$R_t = \sum_{i=1}^{5} R_i \tag{2.10}$$

Product investment cost I_i for that year was given by the number of new product lines multiplied by the cost of adding a product line D_i, divided over the number of years Y the company plans to pay off the investment as shown in equation 2.11.

$$I_i = L_i * D_i / Y \tag{2.11}$$

The total investment I_t for the company was calculated by adding all the investment costs from the individual lines as shown in equation 2.12.

$$I_t = \sum_{i=1}^{5} I_i \tag{2.12}$$

The total number of sales Q_t was calculated by adding the five product line sales together as shown in equation 2.13

$$Q_t = \sum_{i=1}^{5} Q_i \tag{2.13}$$

The number of employees E was determined to be a function of how much work was available which was given by the quantity sold. The number of employees was defined as the total quantity sold in the company divided by a fixed number of quantity sold per employee. The company stated that the parameter that increased their need for employees was more sales. Based on their current setup 8000 sales were assumed. The employee calculation is shown in equation 2.14.

$$E = Q_t/8000 \tag{2.14}$$

The inventory Y was calculated as a small fraction of the total annual quantity sold comparable to their current sales to inventory ratio. This is shown in equation 2.15.

$$Y = .05 * Q_t \tag{2.15}$$

The office floor size F was calculated such that it allowed a given square footage per employee and a given square footage per inventory item shown in equation 2.16.

$$F = E * 400 + Y * .375 \tag{2.16}$$

The office cost C was simply an annual rental square footage cost per month multiplied by the calculated office size in terms of square footage multiplied by 12 months as shown in equation 2.17.

$$C = .75 * F * 12 \tag{2.17}$$

The total salary cost S_t was calculated as the sum of the salaries of each employee. The salary S of each employee was assumed to be \$75000. This is shown in equation 2.18.

$$S_t = E * S \tag{2.18}$$

For further information on the optimization code, including the equations for the other product lines, refer to the URL in Appendix A.3

2.4.3 Problem Constraints

In total sixteen constraints were needed to run the optimizer. The constraints focused on important business details as well as other aspects necessary for the optimizer to run correctly.

The constraints related to business operation included a maximum yearly office cost, a maximum yearly salary cost, a minimum number of employees, and a maximum annual product investment cost. These are shown in equations 2.19, 2.20, 2.21, and 2.22 respectively. The advertising cost was also constrained to be 11% of the total gross revenue which has been shown to be an optimal percentage [54]. These constrained equations were defined to encourage sustainable growth of the company since growing too quickly can be detrimental to a business [55].

$$C < \$35000 \tag{2.19}$$

$$S_t < \$350000 \tag{2.20}$$

$$E > 3 \tag{2.21}$$

$$I_t < \$100000 \tag{2.22}$$

Other constraints used which were required only for successful optimizer operation included the quantities sold, salary costs, and revenue had to be positive. Also, the markup multiplier used in calculating the markup ratio must be greater than zero, and the total percentage of advertising costs for the different product families needed to sum to 100%.

Constraints were also used to ensure the optimizer operated within reasonable limits and provided other constraints on the business operation. These bounds provided limits on advertising, number of product lines that could be added per year, markup ratio, and percentage of advertising cost that could be used per product family. The lower bound for product lines per family is the current amount of products for a given category (it is assumed that no cost is required in research and development of existing product lines). The upper bound for product lines per family is two more than the lower bound (except for the bariatric chair which only has the current design that can be added). Two is considered the maximum number of product lines that can be added in a year for a product family due to resources and time required for development. The upper bound for advertising allocation to a single line is 80% assuming all of the advertising should not be spent on one line.

2.4.4 Optimization

While it is possible to attempt a multi-objective optimization through maximizing revenue and minimizing expenditures, a single-objective optimization to maximize the companys profit was deemed sufficient. This approach retains both the aforementioned desired objectives of minimizing expenses and maximizing sales revenue while only using one objective in the optimization. By reducing the number of objectives to a single-objective problem, a relatively simple constrained optimization was able to be utilized to maximize desired profit. The total profit P was calculated using outputs from many of the previous equations as shown in equation 2.23 where A_t is total money spent on advertising and T_t is the total material cost.

$$P = R_t - I_t - A_t - T_t - C - S_t \tag{2.23}$$

An optimizer was used to vary the inputs while adhering to constraints to find optimum input values to maximize profit of the business. The gradient-based sequential quadratic programming (SQP) algorithm was used within this optimizer and provided an optimum within 19 major iterations and 343 function calls. For this application, the fmincon optimizer in Matlab® [41] was implemented. The optimizer converged to a single solution consistently which suggests a properly formulated problem that avoids ill-conditioned functions. Design variables and constraint scaling was used to provide improved optimizer performance.

The outputs of the optimizer included optimum values for total advertising expenditure and product lines added, markup percentage, and distribution of advertising funds in each of the four product families. Other outputs calculated by the optimizer, which were not design variables but provide very useful information to the company, included the yearly projected profit, number of employees, inventory amount, office costs, and salaries of each employee.

The problem included four product lines, with the fifth for the bariatric chair modeled later using a similar formulation as the previous four. The chair had no prior sales information to base its markup ratios and advertising effectiveness, so similar models to a comparable product line were used. This line was scaled down to about one-twentieth comparatively, because of an assumed lower demand for the bariatric chair.

Once the chair CAD models were built, the optimizer took in the output values that were previously generated by the designed chair and calculated the outputs for the business based on those parameters. These parameters affected the base cost of the product as well as added or removed value depending on whether or not the design met certain market requirements. Doing this, the decision maker could change the chair as much as they wanted and could see the changes it would make in the business each time the optimizer was run.

2.4.5 Business DSS Description

The business DSS has two main parts used for finding the optimal inputs for the business: the inputs and outputs sections.

The inputs of the business DSS contain slider bars to change various input parameters shown in detail in Figure 2.9. The input parameters include:

- Total advertising expense
- Products in each specified line
- Sales markup from cost of goods
- Advertising split among the five product lines

The five product lines are the support stop, toilet seat, hygienic sprayer, window, and bariatric chair lines. After the optimizer has completed, the decision maker is able to see the values for the optimal solution to the right of the initial values to facilitate comparison. The user also has two buttons that can be used. The first is the “Set Inputs to Optimal” button, which sets the inputs to the optimal values that were recently calculated. The second, “Reset Inputs” button, can reset the the slider bars to the middle values.

The outputs of the business DSS shown in Figure 2.10 include information to make a more informed decision on whether or not to add the chair. The outputs include projections for profit, revenue, advertisement expenses, materials cost, office cost, salary cost, inventory quantity, total employees, and total products sold. For further help with deciding specifically what to do with the chair, there are outputs for the chair’s cost, revenue, profit, years to pay off, and quantity sold. These are all based on a one year time frame. The optimized values for each of these outputs is also

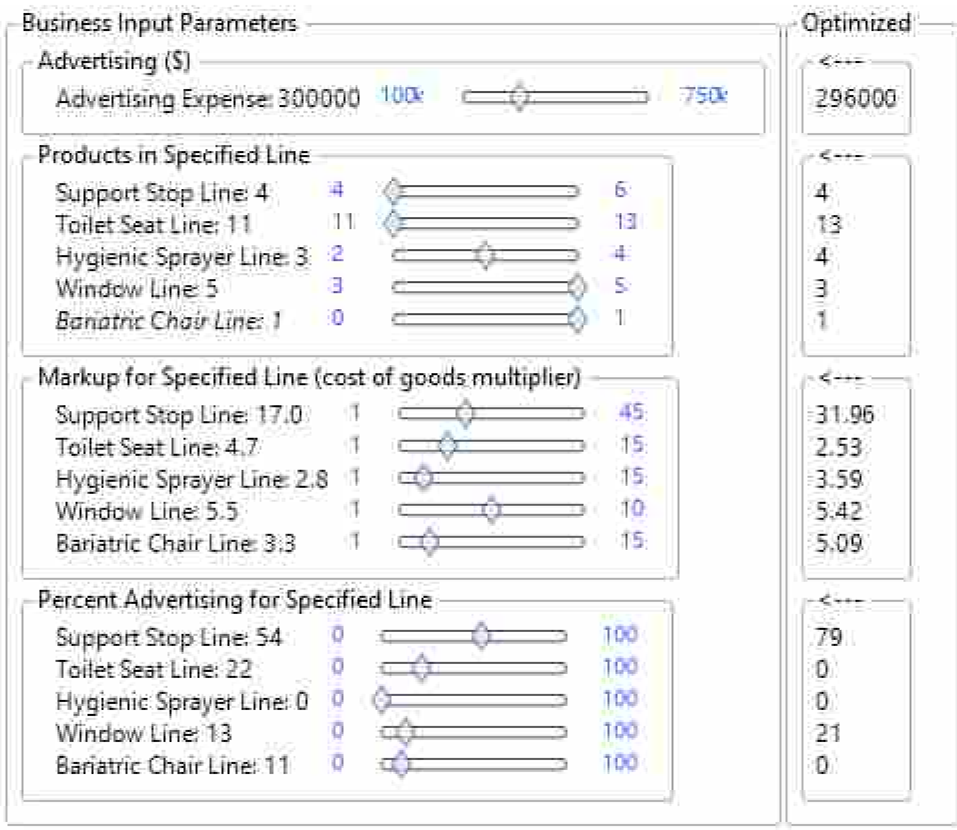


Figure 2.9: The input section of the business DSS and optimization platform

shown after the optimizer button is clicked. Similar to the PDG, the decision maker has the ability to save their inputs and outputs by clicking the “Save Business Values” button and can reload those saved values at any time by clicking the appropriate load button.

With the input and output section of the business DSS combined, there is a useful way to iterate on business values to facilitate faster analysis than unprocessed data. The entire business optimization platform is shown in Figure 2.11

2.5 Monte Carlo Analysis

A Monte Carlo analysis with 500,000 different scenarios was executed for design exploration. Within this section, decision makers are able to view a scatterplot of all the preprocessed data with an x and y axis of their choice for inputs and outputs. They can then select points of interest in the scatterplot and push the data from the selected point back into the System DSS to see

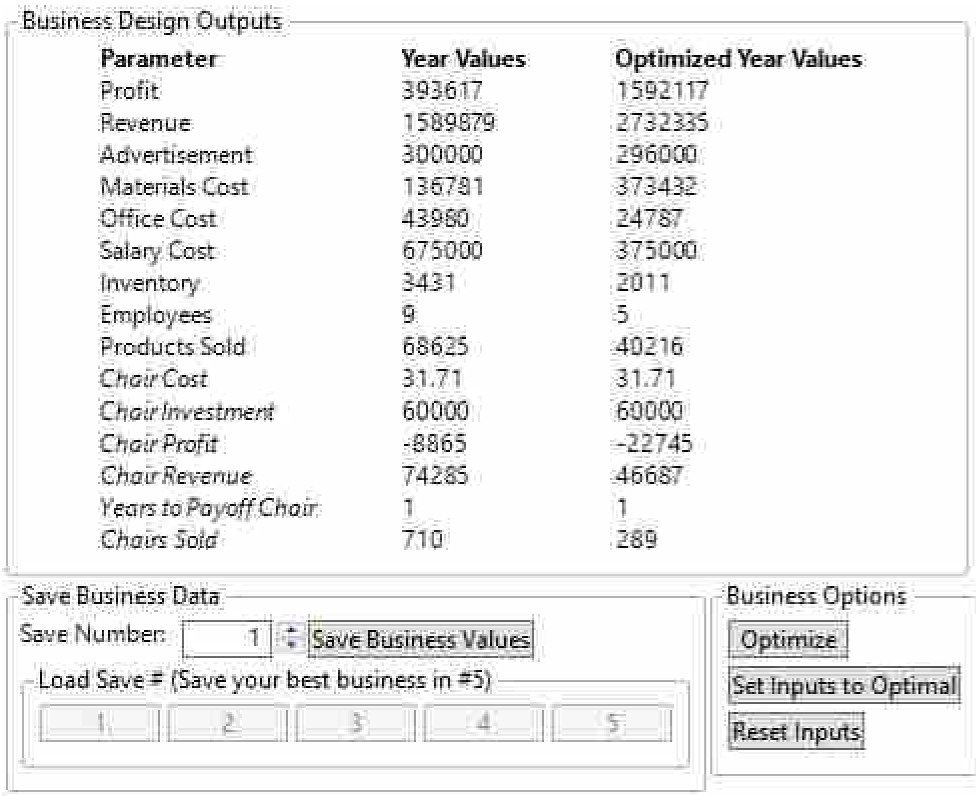


Figure 2.10: The output section of the business DSS and optimization platform

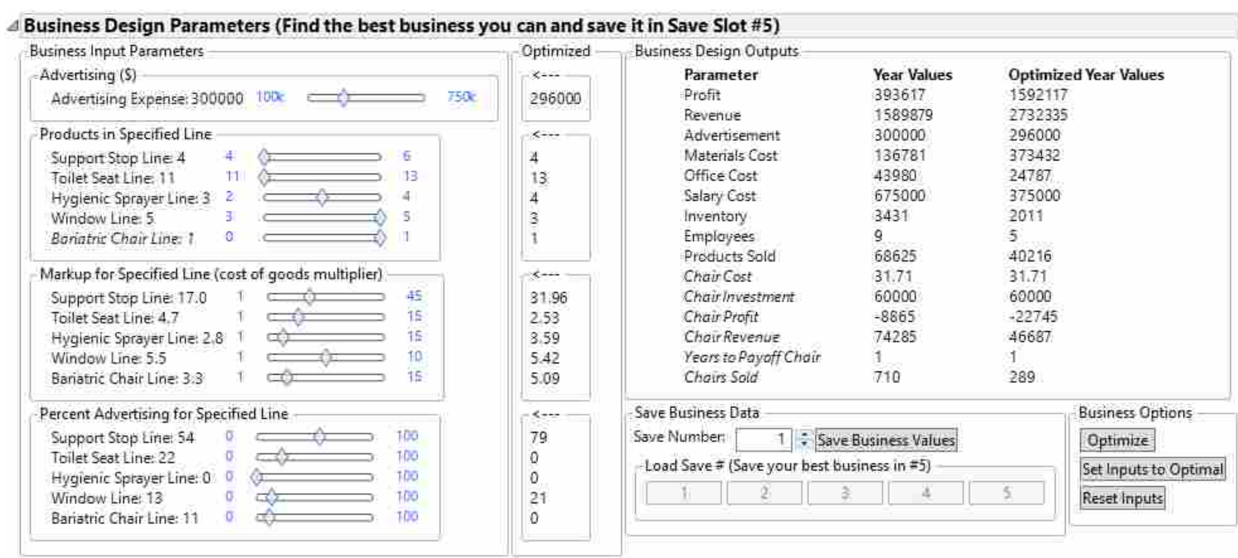


Figure 2.11: The input and output sections of the business DSS and optimization platform

what system model was used to create that point. This enables a variety of design space analyses.

A Monte Carlo was chosen to enable an exploration of both good and bad designs rather than just the trade-space with points along the Pareto frontier. With a view of the design space users could see trends in the data, especially when the ability to color the scatterplot by a third data set was added as an analysis factor.

2.5.1 Input and Output Parameters

Figure 2.12 shows 27 different inputs possibilities and 20 outputs possibilities. Along with this, the decision maker has the ability to color the graph with any of those 47 variables. This allows a considerable amount combinations that can be explored, which allows for further insight into the data. As the decision maker change these parameters the scatterplot updates in near real-time to help them better understand the design space. Four examples of these combinations are shown in Figure 2.13.

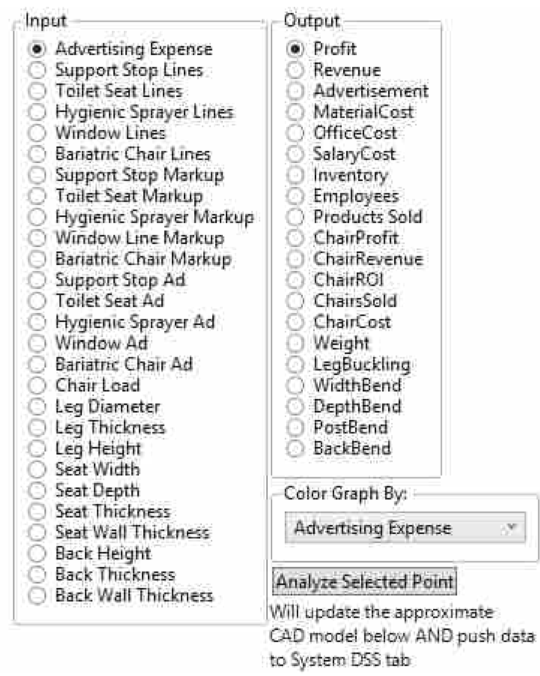


Figure 2.12: The inputs and outputs for the Monte Carlo analysis are shown here

Decision makers are able to then select any point on the scatterplot and select the "Analyze Selected Point" button to get the data that is contained in that point. The image of the chair at that point automatically updates on that page. The remaining data is pushed into the System DSS if

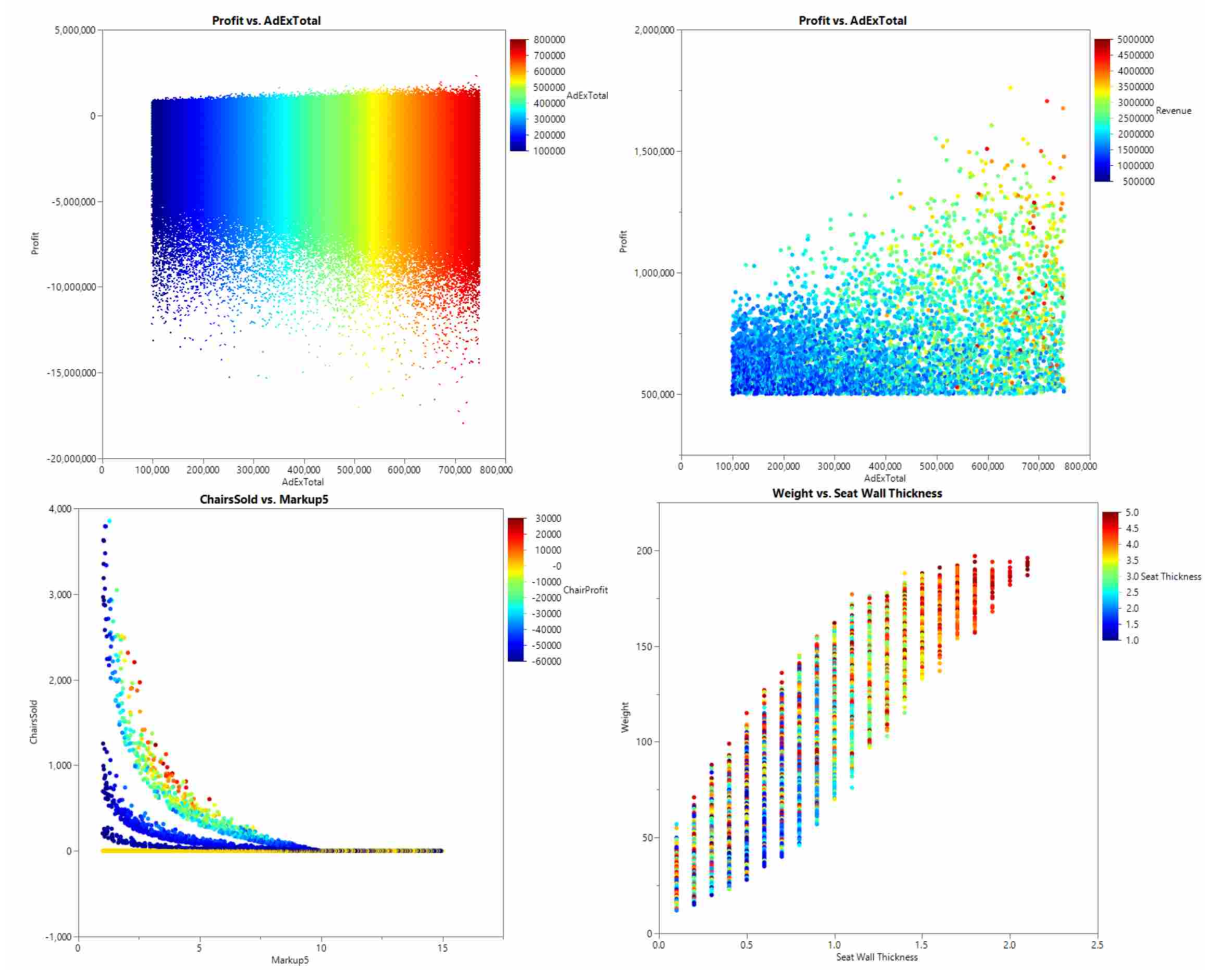


Figure 2.13: Four out of the thousands of possible design analysis scenarios using the Monte Carlo analysis

the decision maker desires to look further into that design. The decision maker can further explore the scatterplot data by selecting different subsets of the data and performing additional statistical tests. The decision maker has the ability to "Hide Unprofitable" which hides all designs that gave less than \$500,000 of profit. They can also "Hide Bad Chair Designs", which would remove those designs that give error messages when created in the PDG. For example, if it chair that does not meet the required factors of safety, it would be removed. Lastly, the decision maker can hide all scenarios that contain both of those conditions. The full Monte Carlo analysis tool is shown in Figure 2.14.

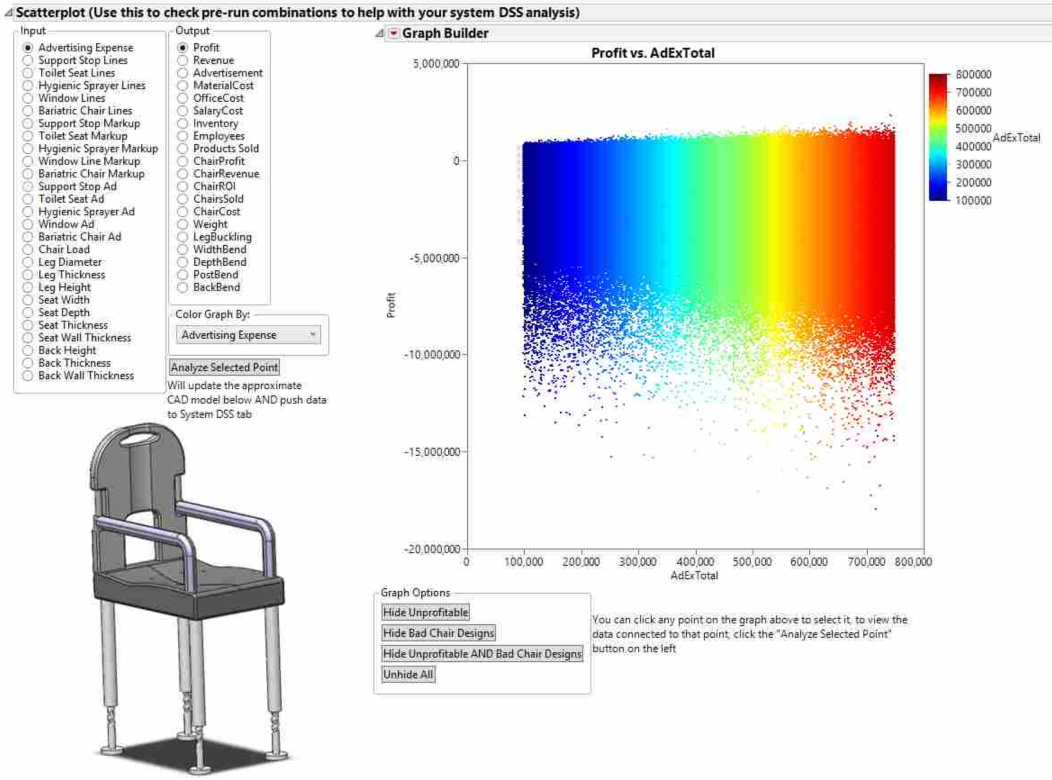


Figure 2.14: The Monte Carlo used to assist decision makers in validating their conclusions

2.6 System DSS

The integration of the business DSS and the product design generator is called the System DSS. The System DSS is developed in JMP to allow interactivity and automatic updating, such that whenever any input value changes it will update any outputs that are affected by it in near real-time. For example if certain input parameters of the chair are changed, the System DSS will changs all affected outputs, including the outputs of the business DSS. The code for the System DSS can be found in the URL shown in the Appendix A.4

The data flow of all of the parameters is shown in Figure 2.15. This is the general flow of all the data passed throughout the entire DSS. If a user only changes a value in the second or third box down then it only flows from there onward. The values in the first box flow through the entire system to affect all of the data.

The fully connected DSS can be used to determine whether or not it is financially attractive to add a bariatric chair line to an existing business. With the integration of all the various subcom-

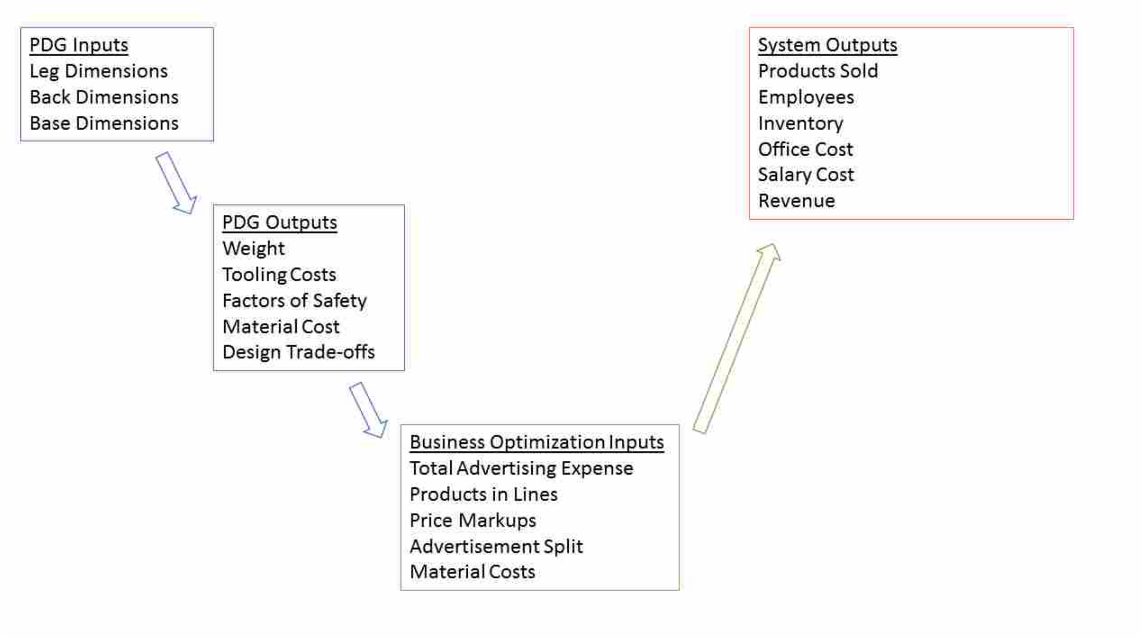


Figure 2.15: A diagram of inputs to intermediate values to final outputs

ponents, the system-level tool is now able to assist users in system-level decisions. A screenshot of the entire System DSS can be seen in Figure 2.16. The Monte Carlo scatterplot is shown on a different tab inside the full system.

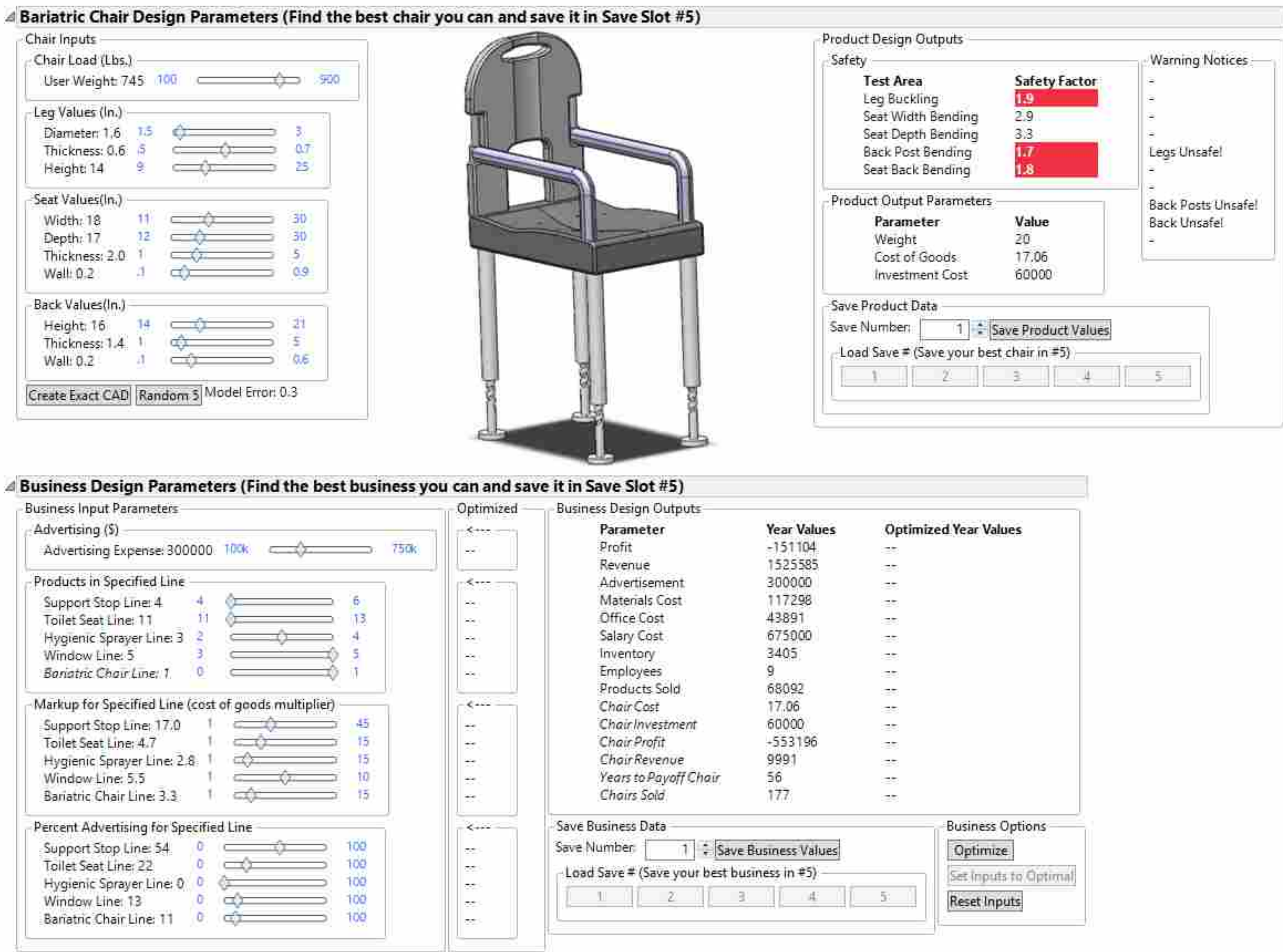


Figure 2.16: The final System DSS with the PDG on top and the business DSS on the bottom.

CHAPTER 3. DSS EVALUATION AND ASSESSMENT PROCESS

Experimentation and tests were performed to see if an interactive System DSS was effective in improving decision making. This was done by providing the DSS to users who were unfamiliar with the product and process to see if they could make a better decision with just the use of the System DSS. The System DSS was presented in a specific manner and survey questions were also given to the user to answer at the conclusion of the experiment. This chapter discusses the following various aspects of the testing strategy:

1. Experimental Procedures
2. Unprocessed Data
3. Design Decision Recordings
4. Survey Questions
5. Event Recordings
6. Data Collection Process

3.1 Experimental Procedure

Tests subjects were to be selected from any number of individuals over the age of 18. There was no needed background or requirement to be a tester for this research other than age and basic cognitive abilities. The test would take place mostly in the BESD Lab on BYU campus, where it was developed. It also could be remotely given to those in reach of the BYU internet network. Testing would take place based on the schedule of the participant which occurred at various times of the day.

The testing started with the decision maker being given one of two different types of tests. The first or "unconstrained" test is the full System DSS including the unprocessed data, PDG, business DSS, and scatterplot. The second "constrained" test is similar except the PDG and business DSS are no longer on the same viewing area, which means a user cannot watch how making small changes in the product directly affect the details of the business metrics. Some interactions cannot be observed because the constrained test is guided, meaning that once a user moves on to the next portion they cannot return and view changes or what was previously entered. Furthermore, the constrained test does not have the Monte Carlo analysis section for further data analysis.

Once the decision maker is given a test, they start by viewing the survey questions for the test, to familiarize themselves on the questions that will be asked at the end. They are given instructions to discover if it is a good idea to add the bariatric chair product line to the business.

The next portion of the test is the unprocessed data portion. During this stage the decision maker is able to look at all the unprocessed data of the company in an Excel sheet. The decision maker can do whatever any analysis with this data that they wish, keeping in mind that they need to decide if it is a good idea to add the bariatric chair. Once they look through this data they can then answer the question if they think it is a good idea to add the chair or not. After this question is answered, they move on to the System DSS. Here they can change values as they desire, and they also have the option of using the Monte Carlo analysis if they are given the unconstrained test. Once they are finished with analysis they answer the questions regarding the tool and how this type of tool was useful or not. Questions were written to try to discourage decision makers from evaluating this tool specifically and focused on the concept and functionality available in this tool.

3.2 Unprocessed Data

The unprocessed data is a simplified record of all the transactions of the company for the past eight years. The information contained in this data set includes all sales of products, including the item category, date, quantity, sales price, and total transaction amount. It also includes the costs spent on advertising, investment in product materials, payroll, and rent, all on the respective days that any transaction in any of those categories occurred. This information was tallied in the excel sheet to give the decision maker some totals, as well as an estimation that it would cost $60,000 to create the tooling for the chair. Additional information was given on equations that could be used to calculate stresses for the chair. The decision maker was told they could do whatever analysis they wanted on the unprocessed data to help with their analysis.

3.3 Parameter Recording

As the decision maker goes through the test they are required to save their final design for the chair and for the business in save slot #5 for each system respectively. This gives, at a minimum, two points that can show what information the decision makers were basing their decisions off. The decision maker has the ability to save up to five designs for each system, meaning that there is a possibility of ten saves that can be used to go back and forth between designs that the decision maker may have wanted to analyze in the future before making a final decision. When the decision maker completes the test, all of the items that are saved into slots are saved to a document that is able to be reviewed to try and draw further conclusions about what the decision maker was thinking.

3.4 Survey Questions

Survey questions were given to the decision maker to read before taking the test and then given again afterwards for them to answer. It was shown before to help them prepare elements of the tool to explore. Again, the questions were aimed at evaluating the usefulness of this kind of tool and not evaluating this tool specifically. The questions also helped see if the research hypotheses were supported. The survey contains the questions shown in Table 3.1.

3.5 Event Recording

For analysis purposes, all of the decision maker's interactions with the tool were recorded by the DSS. As each decision maker used the DSS, all mouse clicks, information entered, and times of these events were recorded. This enabled observation into any patterns of the decision maker's interactions with the tool. Also this data can be analyzed to see if decision makers spending time on certain sections was more beneficial than using time on others. It could also be ascertained if and where the user was confused while

Table 3.1: The survey questions given to all testers

#	Survey Questions
1	The tool is interactive in such a way that I was able to make effective trade-offs between the business and product.
2	The tool helped me make effective decision on which product to design.
3	The tool helped me find better solutions than the unprocessed data.
4	The tool is structured in a way that it helped with making system level decisions.
5	Business and engineering data are connected in such a way that the interactions between the two can be seen.
6	The integration of the engineering and business system into one GUI improved my decision making ability.
7	I was able to analyze more possibilities for designs using the tool than over the unprocessed data.
8	The tool saved time over using the raw data.
9	The DSS help me gain a better understanding of the effect of product design on a business.
10	What did you find most useful in the DSS?
11	Is it a good idea to add the bariatric chair line? Why or why not?
12	How does the overall business change as individual parameters are changed for the chair?

taking the test. Using this information more conclusions can be made about the usefulness of the tool and the different test types. A visual of the recording is shown in Figure 3.1.

3.6 Data Collection Process

Data was stored automatically when the decision maker clicked the button to say that they were finished with the survey questions. The data was saved into four files, the first showed their basic answers from the survey questions, time required to finish the test, and the written answer from the unprocessed data portion, along with their name and the date. The second file contained all their saved answers from the PDG portion of the test. The third is similar to the second except it contains all data from the business DSS. The fourth file contains the time stamp information which is the time of the click and the value entered from that click or from typing.

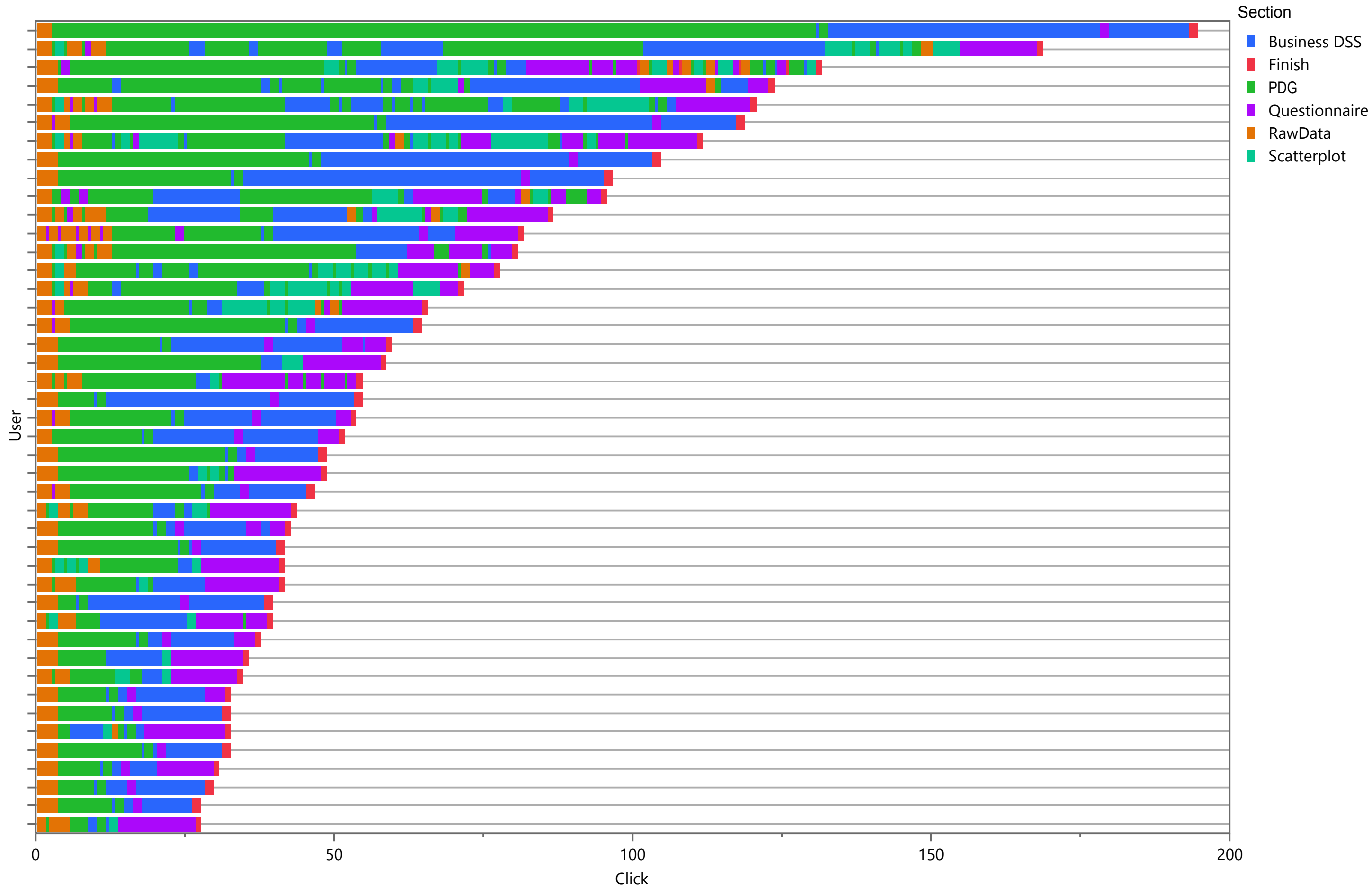


Figure 3.1: Users' clicks and in what section of the DSS they were made are shown in the order they were clicked

CHAPTER 4. RESULTS AND ANALYSIS

This chapter presents some of the key findings from the user testing described in the previous chapter. Various conclusions and observations are made that support some of the hypotheses and answer some of the questions previously presented in Chapter 1.

4.1 User Testing Sample and Time

A majority of the test subjects or "decision makers" were college students in the 18-27 year-old age range due to availability at BYU Campus. Although the age and skill level may have some effect on the results, and many of the users' work experience differs from someone in industry who has been working for much longer, the difference in experience should not significantly change the outcome of the study.

There was a total of 44 testers who volunteered a combined total of 15.11 hours to evaluate the data and System DSS. The average decision maker took 20.60 minutes, the longest 55.07 minutes, and the shortest 8.80 minutes.

4.2 Unprocessed Data vs. System DSS

Using the unprocessed data, most decision makers made no additional analysis to the dataset but made a decision based only on the information they were given. A few decision makers summed up items that were not explicitly stated like total expenditures, but that was the most anyone did as far as further analysis. In general, decision makers looked at the company and how it was performing and decided if it was a good investment with little to no quantitative analyses. The data indicated that the company was doing well over the past eight years with consistent growth in revenue and profit each year. Many of the testers stated it would be a good idea to add a new product based on the fact that the company had previously been doing well. One user states when asked if the chair should be added, "Yeah. The Profit seems high enough that you might as well go for more!" This attitude was similar among other users.

A large number of other users stated that there was not enough information to gauge the demand for this sort of item. When asked the same question, one user stated, "No, because there is not enough evidence that there is demand for this product." which was also a common answer. A measurement was taken of each user's confidence in their answer where a 0 indicates they had no confidence, 1 they had some confidence, and 2 meant they were fully confident. This was then compared to the confidence of those same users after they had used the System DSS. The results showed that the decision makers were statistically more confident with a p-value of .021 after using the system portion as shown in Figure 4.1. It is important to note that the increased confidence did not necessarily result in a better answer, since adding the chair cannot be proven perfectly to be a good or bad decision because of the uncertainty in future markets. However, there was enough information to suggest that it could be profitable within two years. Still, a business owner could choose not to add this chair regardless of this fact, and it would not necessarily be a bad decision.

Using the unprocessed data 73% of the users came to a conclusion. 59% of people would add the chair and 14% would not. After using the System DSS 45% of the users changed their answer. In the end 61% of people would add the chair, 30% would not, and 9% still did not know. After using the System DSS 91% of decision makers came to a conclusion. Meaning that 75% of people were able to make a decision after using the DSS who beforehand were unsure. With 45% of users changing answers, the data suggest that users were not sure of their original decision using just the unprocessed data. With the System DSS they were able to analyze information that caused them to change their answer, which further supports the confidence they were able to gain after using the System DSS. In the end most people decided to add the chair to the business. The distribution of choices and the changes of choices is shown in Figure 4.2.

4.3 Parameter Recording Analysis

Using the parameters that were saved, analysis was possible on how the decision maker performed using the tool. The final answer for whether or not to add the chair could be justified as a good or bad idea depending on many different factors, and either could be the right answer. The data suggested that it might not be a bad choice because it would pay itself off within 2 or 3 years. Some users deemed this to be too slow while others thought this was a good investment. The tool's purpose was to help the user make a decision, not to make the decision for them. Regardless, correctly using the tool to make good choices was something that could be analyzed. For example, did the decision maker create a chair that was optimal to the situation? Some of this was based on opinion, but there were some designs that were dominated by others. For example a chair that would break if a 500 lbs person sat on it was clearly not a useful design while there were many other designs that could accomplish this requirement. Each decision maker's final save was analyzed to see if they chose an optimal solution. For the product this meant that they designed

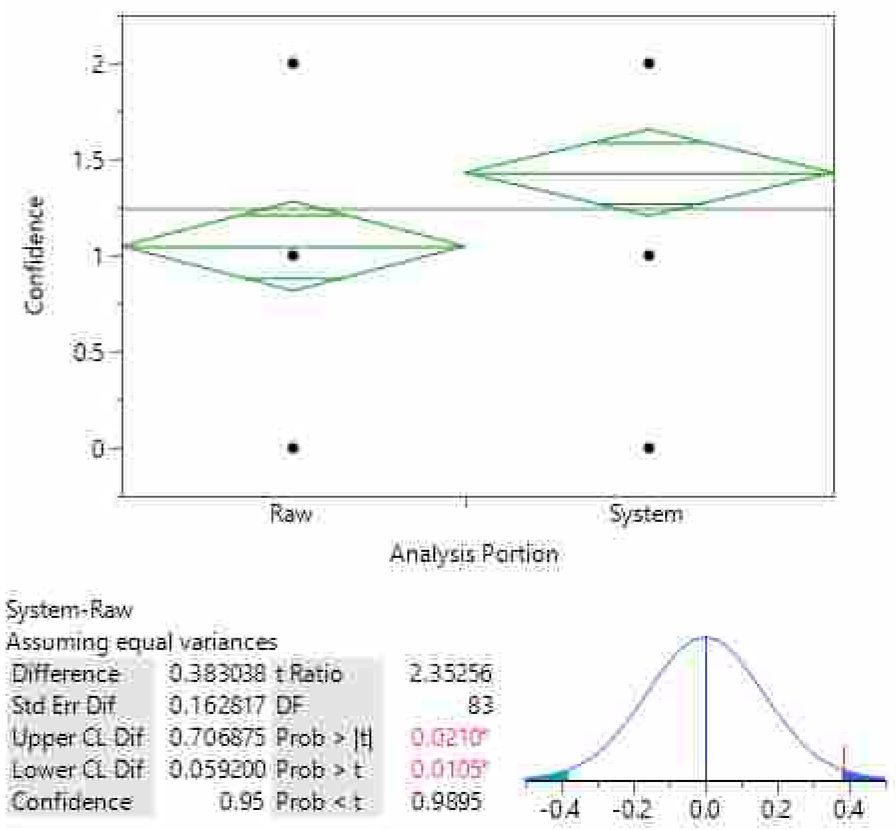


Figure 4.1: Significance between the decision maker's confidence after the unprocessed data and then after the System DSS portion of the test

a product that had no errors which would cause it to either break, not fit in the tub, weigh too much, or have unsuitable dimensions. For the financial side it meant that the decision maker created a business that was not significantly worse than the value the optimized business would give. In Figure 4.3 it is seen that 77% of decision makers made an optimal analysis of the chair and 73% of decision makers made an optimal analysis of the business meaning that their profitability was over $1,000,000 for the year. Of all the decision makers, 57% made an entirely optimal analysis meaning they had an optimal chair and business saved when they finished their analysis. This is interesting because it shows that most of the users were able to make a good analysis on something that they had known nothing about in as little as eleven minutes. One user reports when asked about the DSS, "I was able to understand the data better when it was presented in the DSS I had a hard time understanding what the data meant before it was presented visually." This was a common response among users.

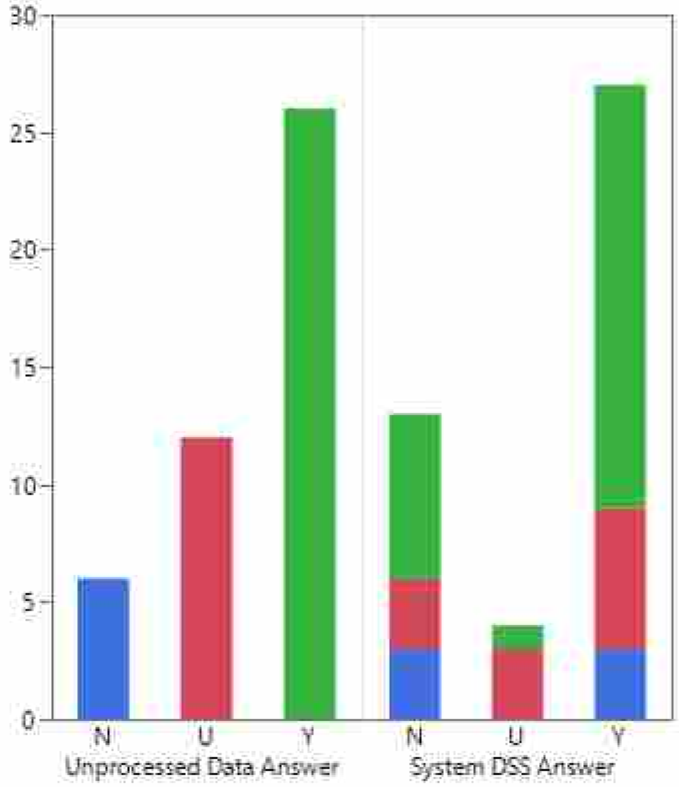


Figure 4.2: The difference between testers' answers as to whether or not to add the chair after using the unprocessed data and the DSS. The change of answers after experimentation with the System DSS is also shown on the right.

4.4 Survey Analysis

As presented in Chapter 3, decision makers were asked 12 questions; three were free response questions and the other nine were questions that were able to be rated using the following scale: Strongly Agree - 5; Agree - 4; Neutral - 3; Disagree - 2; Strongly Disagree - 1.

The survey questions and the average rating for each question is shown in Table 4.1.

Each of these questions was linked to one or more of the initial hypotheses and conclusions can be drawn from this information. It was found that a decision maker could see the interactions between the business and the product design. One tester stated, "I thought the interaction between business and engineering data was very helpful in seeing the connection between the two." It was interesting to note that comments like these were found for both system tests even though there was less of an interactive view in the constrained version of the System DSS. Furthermore, in regards to the tool improving the user's decision making ability, one user states, "I liked being able to

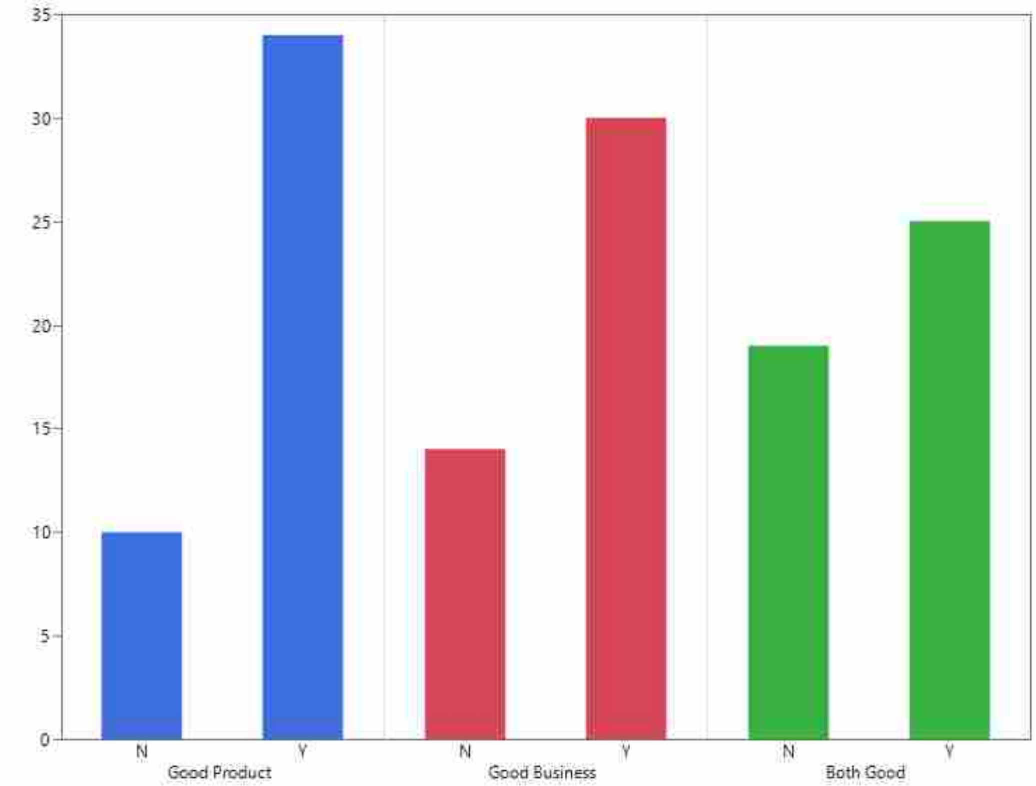


Figure 4.3: Proportion of decision makers who made optimal decisions in the DSS.

manipulate the product and the allocation of funds. It was useful and allowed me to make a better decision."

Based on the high average rating for some of the questions, it was observed that decision makers found the tool to be more effective than using the unprocessed data. Decision makers also found that they had a better view of the system with the DSS than with the unprocessed data. Based on the survey responses, many of the hypotheses about the System DSS were in general supported, meaning the System DSS was more effective in assisting a decision maker find an accurate answer.

Since each of the decision makers were presented with one of the two treatments for the System DSS (constrained or unconstrained), the differences in answers to the questions across the two groups could be ascertained. As shown in Table 4.2 it is seen that only one of the nine questions from the survey questions showed statistical difference in the answers. The first question (QV1), regarding trade-offs, showed a statistical difference between the perceived interactivity of the constrained and unconstrained System DSSs.

Table 4.1: The average rating for the survey questions from all testers

#	Survey Question	Average Rating
1	The tool is interactive in such a way that I was able to make effective trade-offs between the business and product.	3.95
2	The tool helped me make effective decision on which product to design.	3.98
3	The tool helped me find better solutions than the unprocessed data.	4.41
4	The tool is structured in a way that it helped with making system level decisions.	4.05
5	Business and engineering data are connected in such a way that the interactions between the two can be seen.	4.16
6	The integration of the engineering and business system into one GUI improved my decision making ability.	4.18
7	I was able to analyze more possibilities for designs using the tool than over the unprocessed data.	4.64
8	The tool saved time over using the raw data.	4.57
9	The DSS help me gain a better understanding of the effect of product design on a business.	4.23
10	What did you find most useful in the DSS?	Open Response
11	Is it a good idea to add the bariatric chair line? Why or why not?	Open Response
12	How does the overall business change as individual parameters are changed for the chair?	Open Response

Table 4.2: The statistical test of differences in the survey questions show that there is no significant difference except in question 1

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-1.5911578	2.9792046	0.29	0.5933
QV1	1.47031475	0.6720907	4.79	0.0287*
QV2	-0.9398053	0.5395799	3.03	0.0816
QV3	-0.4435479	0.5836023	0.58	0.4472
QV4	0.90043813	0.7062835	1.63	0.2023
QV5	-0.5143309	0.6096848	0.71	0.3989
QV6	-0.6749792	0.8244355	0.67	0.4129
QV7	-0.2421414	0.6167869	0.15	0.6946
QV8	0.47292135	0.8197723	0.33	0.5640
QV9	0.42338611	0.5381827	0.62	0.4315

For the other eight questions requiring numeric ratings, the difference between the two treatments was statistically insignificant with p-values of greater than 0.05. However, the p-value for question 2 (QV2) was comparatively lower than the other questions suggesting a potential correlation with a perception of making better decisions with DSSs that are more integrated (i.e. unconstrained).

This may suggest that providing access to all data concurrently and allowing decision makers to return and explore parameters, make changes, and perform "what-if" analyses quickly, supports a higher-level of confidence in their ability to comprehend the design space and make design decisions.

Finally, it was interesting that Question 5 did not show significance because of the close nature and wording of Questions 1 and 5, both which addressed the interaction between the two major elements of the System DSS. No difference was expected for the other six questions which addressed more specifically the differences between the unprocessed data and the System DSS.

4.5 Event Recording Analysis

Using the timestamp data, a variety of tests were performed, many of them involving how many clicks decision makers made or what things were being clicked. The items and their rankings on how many times they were clicked in total throughout all of the testing is shown in Figure 4.4. There is also a view of the clicks in the different test types shown in Figure 4.5 and an example of a single user's click distribution shown in Figure 4.6. Viewing the clicks on the different sections of the test, it is seen that the System DSS is used the most followed by the some of the parameters that are within the PDG (i.e. the chair parameters). It is interesting to note that more clicks were made analyzing the chair than the business, and more people made a better analysis of the chair than the business.

It was explored if the amount of clicks and the time took using the tool made a difference on the answers they made. Results indicate there was no significant difference between time or clicks taken on the DSS vs. quality of the answer as shown in Figure 4.7 where -1 means that neither the PDG or business DSS had optimal values saved, 0 means they had one of the two systems analyzed well, and 1 means that both of their analyses were optimal. It can be seen in the figure that there are three circles on the right side. The more a circle is overlapped the less chance that

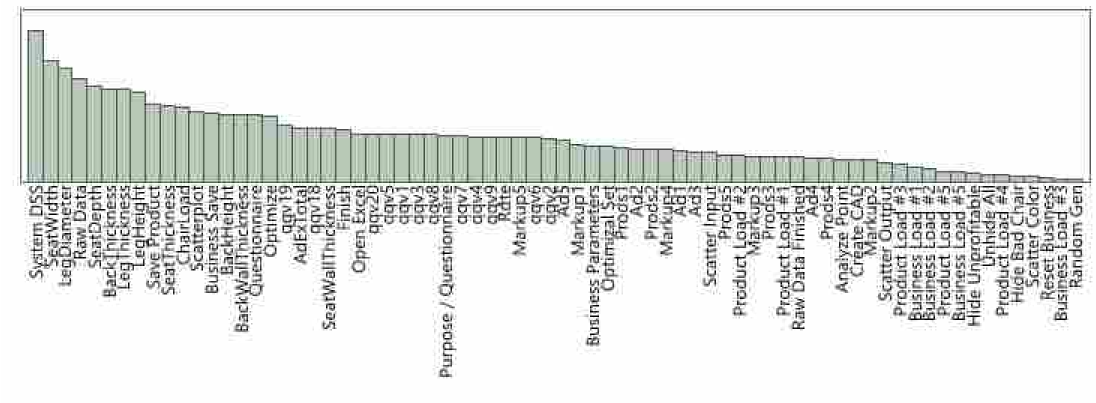


Figure 4.4: A total distribution of what items were clicked in the DSS

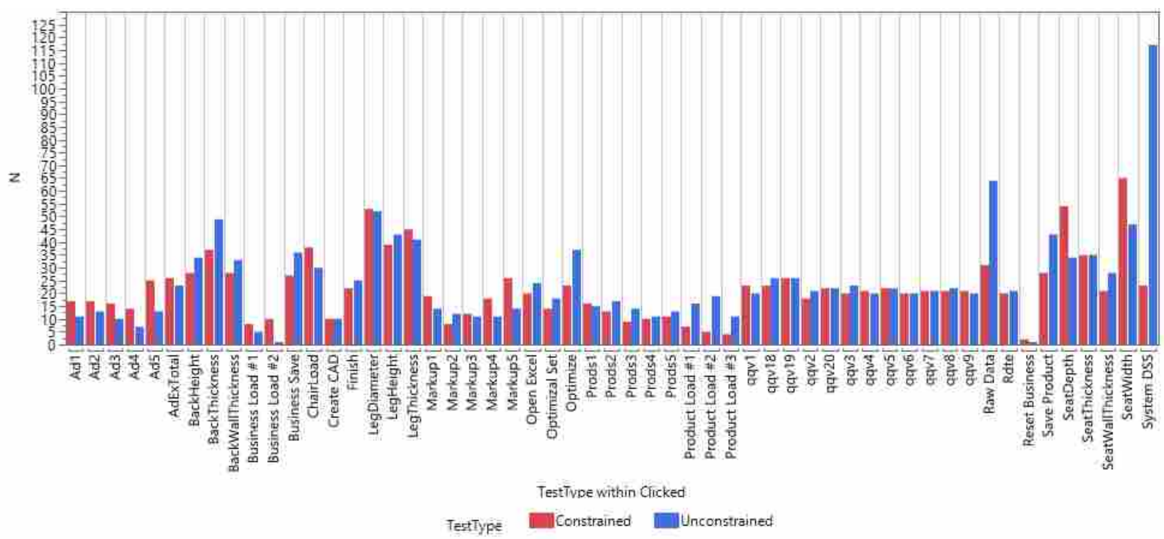


Figure 4.5: A distribution of what items were clicked in the DSS among the two tests

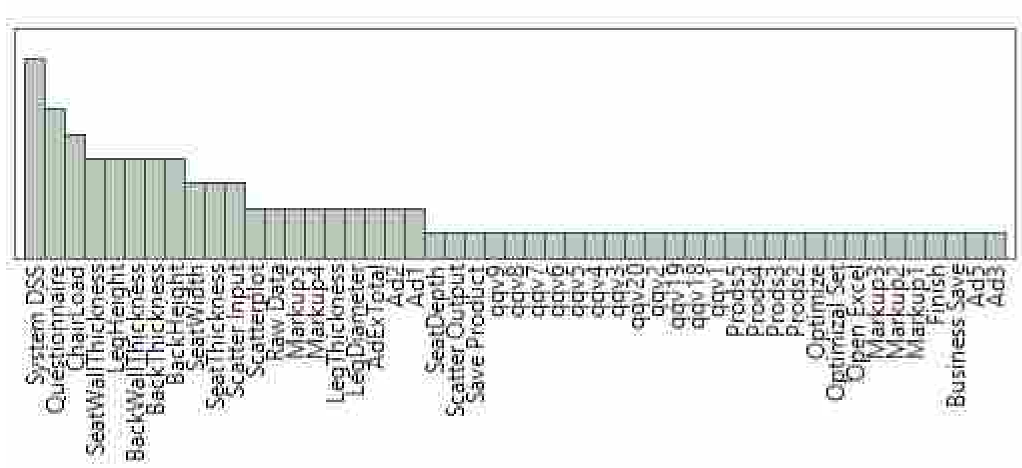


Figure 4.6: A distribution of a single user's clicks in the DSS

it is statically different at a .05 p-value, whereas circles that are not touching would certainly be different. It is interesting to note that the users who took the most time and made the most clicks did not have completely optimal solutions. Although inconclusive, this suggests that perhaps they may have been confused in their analysis and additional tests could be preformed in the future to identify this trend. It is also interesting to note the users who made the most clicks and took the most time are not the same users. Finally, it can be seen in the unconstrained test, users liked to flip back to the System DSS tab after looking at other tabs. Data also suggests that the unconstrained users clicked the optimize button more often, which may suggest that they were making changes to their chair and wanted to see how its analysis would optimize the business. This process was not permitted in the constrained version of the test.

The distribution of time and clicks for all the decision makers is shown in Figure 4.8. Some decision makers made as few as 28 clicks while others made as many as 195. This information along with all of the decision makers times and clicks is shown in Figure 4.9.

An analysis was performed to see whether or not there was a difference between the times in-between clicks for the two test types and also if there was a difference in the optimality of the test results by the amount of clicks made per minute. It was found that both of these turned out to be insignificant as shown in Figure 4.10. From the testing performed on time or clicks taken there is no significance which suggests that users ability for analysis could not be measured by the time taken or interactions with the tool.

There was also analysis performed to see whether there was a correlation between the test times and the number of clicks, as shown in Figure 4.11. This shows something contrary to what might be assumed, that it would seem that the more clicks that were made the more time it would take to make the clicks. However, the correlation is only .23, which means that there is not a very strong relationship.

The final test performed using the event recording data was a test to see whether or not the users spent their clicks in a manner that was statistically different when using one test variant or the other. It was found with a p-value of less than .0001 that there was a difference between the two tests as far as what the user was clicking. This is shown in Figure 4.12. The was an interesting finding because it showed that the users had different focuses as they used the two different tests. It is seen that the constrained users spent a lot more time clicking parameters that

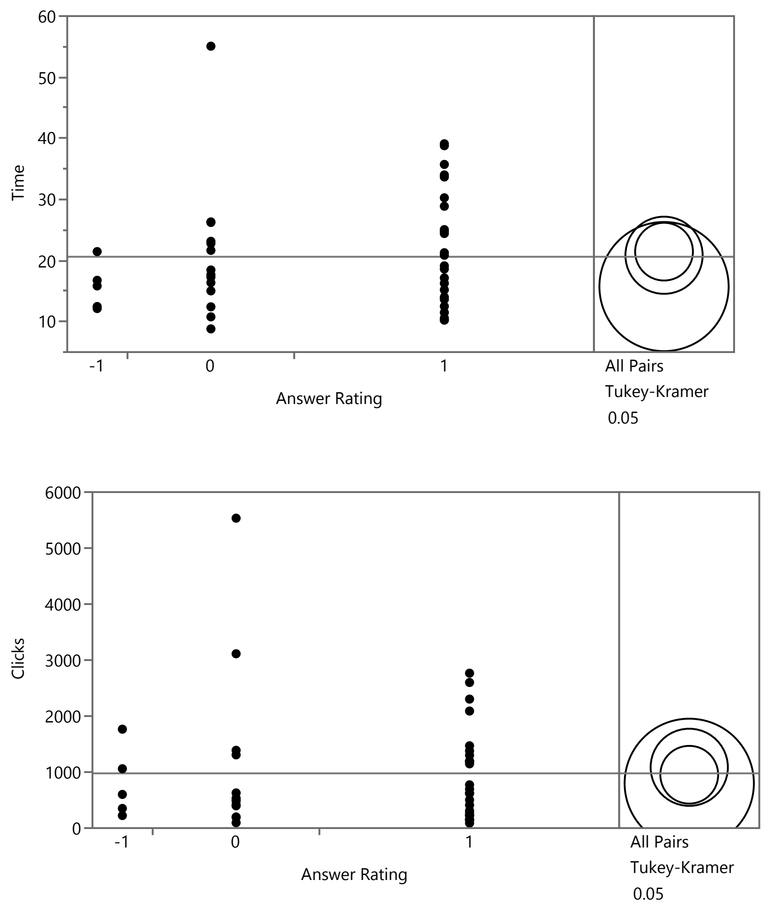


Figure 4.7: A Tukey-Kramer test analyzing the correctness of decision makers' answers compared to the time and clicks taken show no significant difference.

were within the business DSS section. This may have been because users felt overwhelmed with all the information in the unconstrained test and the business section was presented on the same page as the PDG, whereas in the constrained test it was on its own tab. However it is also seen that users with the unconstrained test looked at the survey questions more frequently, which might suggest that they were more interested in what they were trying to answer than the constrained users.

4.6 Constrained vs. Unconstrained DSS Analysis

A contingency test was also made on whether or not having an optimal or non-optimal solution was dependent on the test type given. This is shown in Figure 4.13. Observing the data

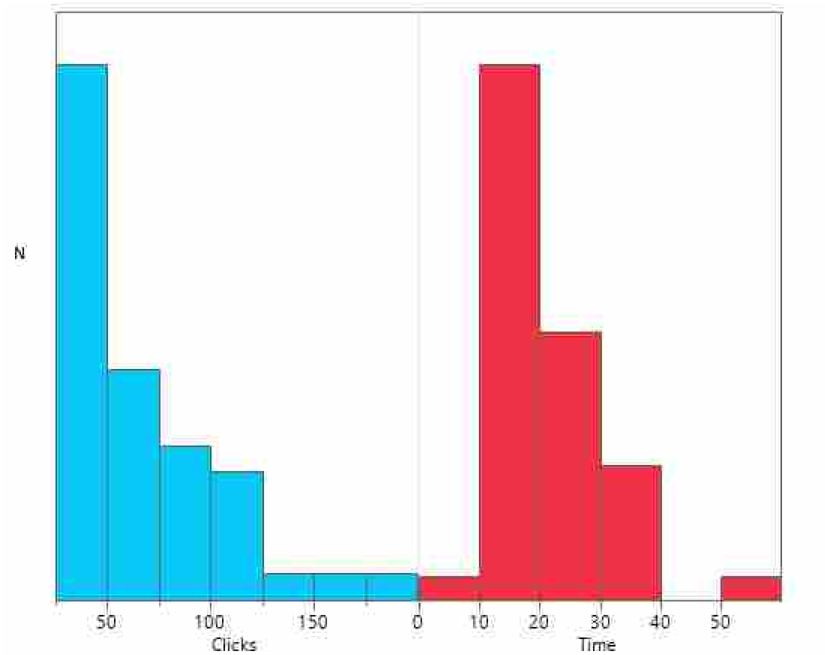


Figure 4.8: A distribution of time and clicks taken for the test

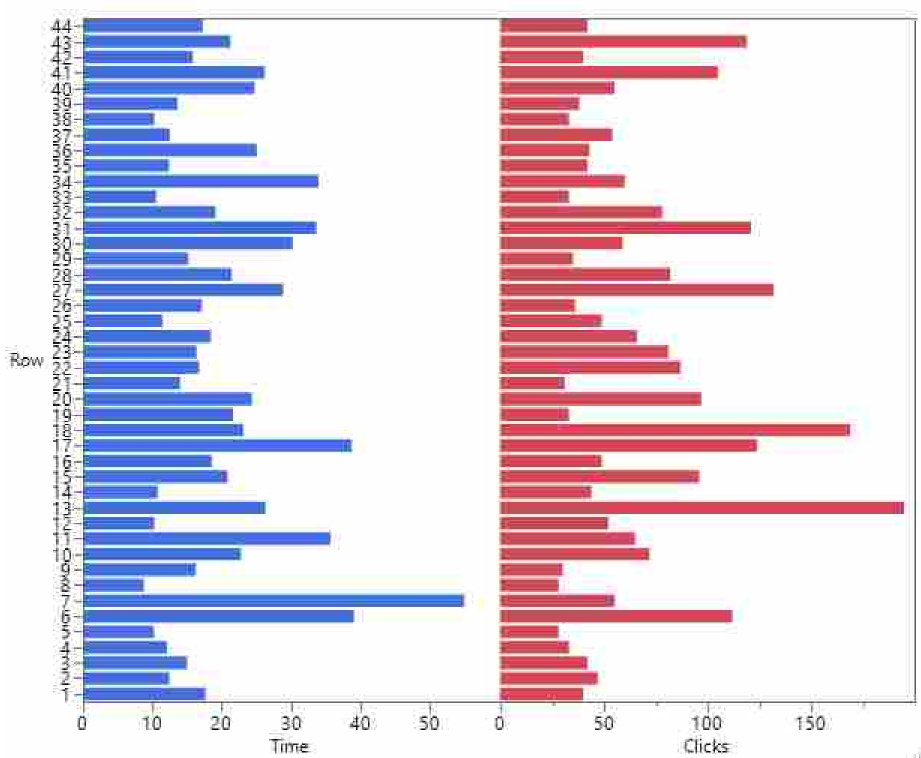
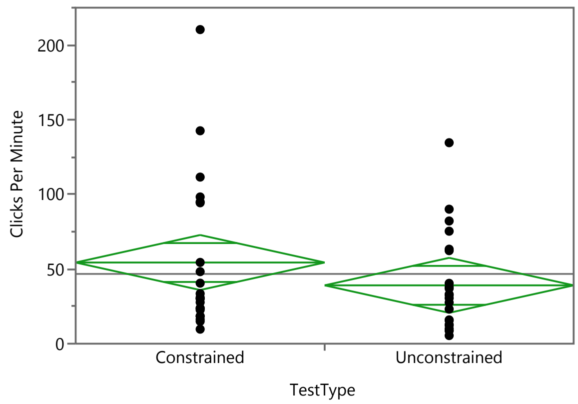


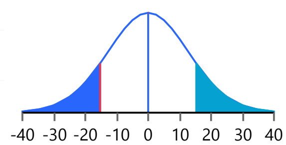
Figure 4.9: Each decision maker’s time in seconds and clicks over the use of the tool are shown

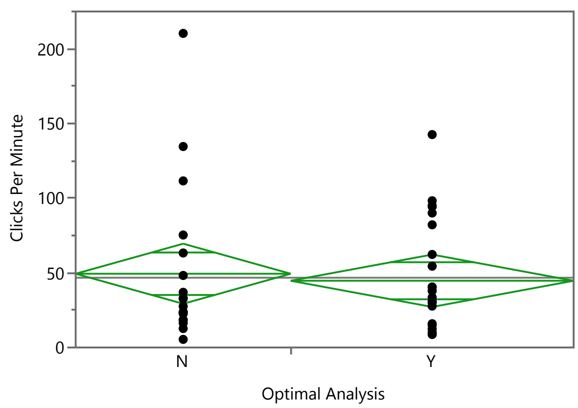


Unconstrained-Constrained

Assuming equal variances

Difference	-15.286	t Ratio	-1.18435
Std Err Dif	12.907	DF	42
Upper CL Dif	10.761	Prob > |t|	0.2429
Lower CL Dif	-41.332	Prob > t	0.8785
Confidence	0.95	Prob < t	0.1215





Y-N

Assuming equal variances

Difference	-4.694	t Ratio	-0.35494
Std Err Dif	13.224	DF	42
Upper CL Dif	21.994	Prob > |t|	0.7244
Lower CL Dif	-31.381	Prob > t	0.6378
Confidence	0.95	Prob < t	0.3622

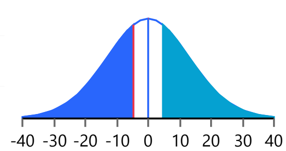


Figure 4.10: The decision maker's clicks per minute tested against the test type and against optimality of results both show that there is no significance

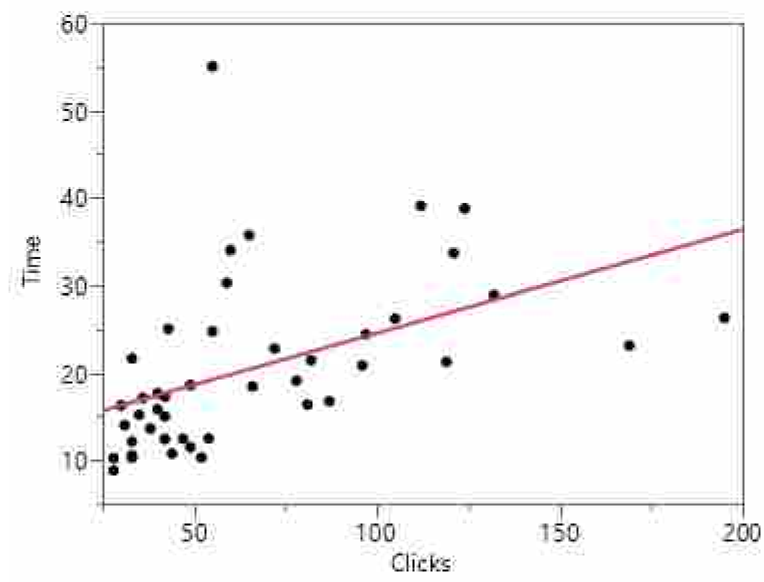


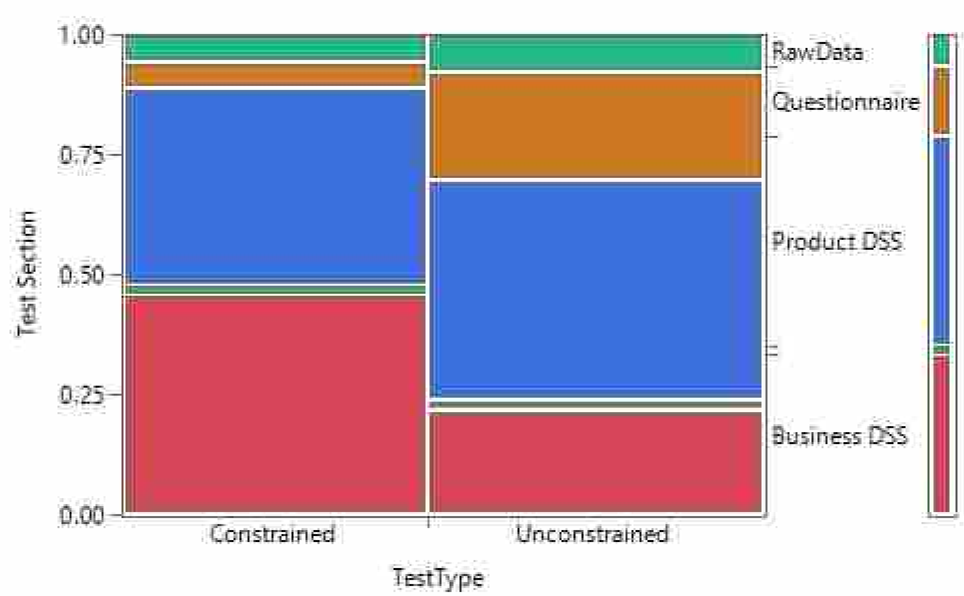
Figure 4.11: There is not a strong correlation between the decision makers clicks compared against the time taken to complete the test

it can be seen that there is no significant difference between the test type and the optimality of the solution.

It was also tested as to whether decision makers had more confidence in their final answers using one test or another. This was done by rating the users written answers, asking whether they would add the chair or not, on a scale of surety where 0 was that they did not know, 1 was somewhat confident, and 2 was fully confident. The results of this test are shown in Figure 4.14. It was concluded that the two test types were not different as far as results were concerned. This was an interesting finding because there are many things different inside the two DSSs which were initially thought to result in a difference.

4.7 Discussion of Results

Reasons for the test not showing any difference may have been that all of the necessary information was passed from the PDG to the business DSS whether or not the decision maker noticed it. This included the base cost of the chair, the investment cost, and all the penalties for poor chair design. Most decision makers designed a suitable chair and moved on to the business optimization portion. Many of the decision makers at this point simply applied the built in optimization feature



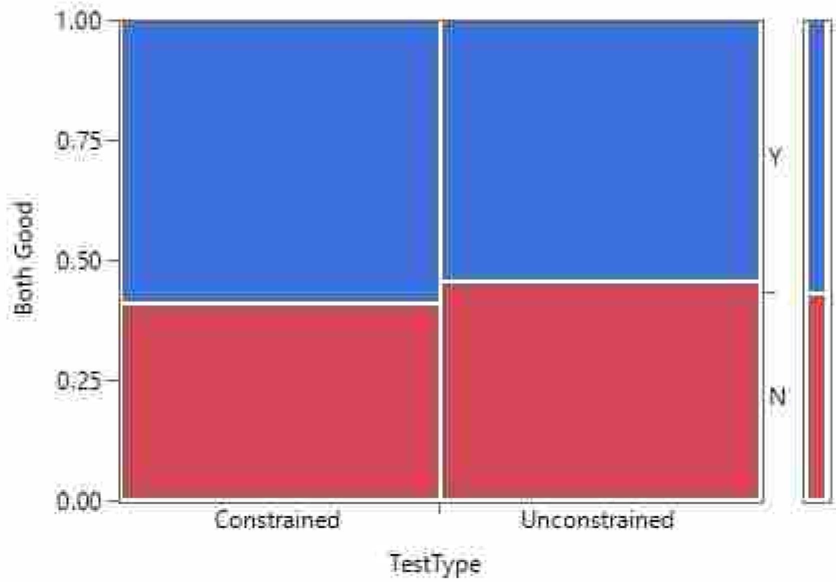
N	DF	-LogLike	RSquare (U)
2739	4	138.86499	0.0403

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	277.730	<.0001*
Pearson	263.575	<.0001*

Figure 4.12: There is a statistical difference between the items that the users clicked between the two test variants, where constrained users clicked the business DSS options more and the unconstrained testers clicked the survey tab more.

which gave them good answers because the optimizer took into account the system interactions. The users were then able to read what the values were and make a decision based on what the optimizer provided. While answering the questions about trade-offs they may have not understood that the two systems were connected even if while changing the parameters in the PDG they could not see how the business was affected.

From analysis it can be concluded by the decision makers rating of this kind of software that the DSS was quite helpful in helping them make decisions. The System DSS would be considered a useful tool, and is much more effective than not having the tool and using different analysis techniques. It saves time and helps the decision makers come to a better conclusion in the end. The DSS provided better answers and allowed decision makers to view interactions that were not able to be analyzed without the tool. One downside to the DSS however, is the time required for DSS development. This leaves the potential developer of a DSS with the questions of: is it worth



N	DF	-LogLike	RSquare (U)
44	1	0.04633329	0.0015

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	0.093	0.7608
Pearson	0.093	0.7609

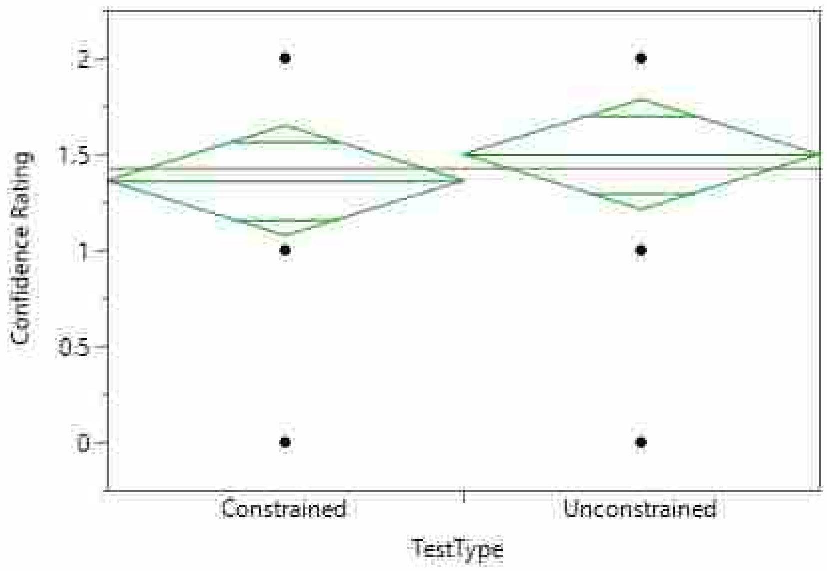
Fisher's Exact Test	Prob	Alternative Hypothesis
Left	0.5000	Prob(Both Good=Y) is greater for TestType=Constrained than Unconstrained
Right	0.7283	Prob(Both Good=Y) is greater for TestType=Unconstrained than Constrained
2-Tail	1.0000	Prob(Both Good=Y) is different across TestType

Figure 4.13: A contingency test showed that the optimality of solutions was not dependent on the test type.

the time to create this tool? Does the time and resources required for development outweigh the benefits gained of a better decision?

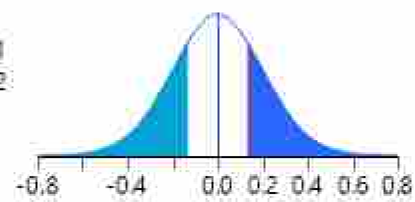
4.7.1 Data Quantity

The absence of variance between the constrained and unconstrained tests encourages asking the question, why was there no difference? One possible explanation is in the potential overload of data that users were exposed to in the unconstrained test. The users in the unconstrained variant were given the extra information contained within the Monte Carlo analysis as well as the ability to interactively view system interactions, which the constrained users did not. Another possibility



Unconstrained-Constrained
Assuming equal variances

Difference	0.13636	t Ratio	0.679781
Std Err Dif	0.20060	DF	42
Upper CL Dif	0.54119	Prob > |t|	0.5004
Lower CL Dif	-0.26846	Prob > t	0.2502
Confidence	0.95	Prob < t	0.7498



Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
TestType	1	0.204545	0.204545	0.4621	0.5004
Error	42	18.590909	0.442641		
C. Total	43	18.795455			

Figure 4.14: User's confidence was tested for each of the test types. There is no statistical significance

for the absence of differentiation in the final analyses is perhaps the information in the constrained test was sufficient to make a fully formulated decision. When users were given the unconstrained test, they used the least amount of information necessary to make an informed decision and moved forward with little interest in doing more analysis than necessary. This would in the end make it such that users would have the same results because they were more or less doing the same analysis, even though some users had freedom to do more.

4.8 Hypotheses Revisited

The original eight hypotheses taken earlier from this thesis are revisited below with information, comments or data that supports these statements. The rating scale for the survey questions was 1 to 5 where 5 was strongly agree and 1 was strongly disagree.

1) "The DSS allows for the understanding of what trade-offs can be made between business and product design". This is supported from the user's rating in questions 1 which spoke about system interactions and was rated at 3.95.

2) "The DSS increases the understanding of the effect of product design on a business". This is supported from answers in question 9 of the survey questions where users agree at a rating of 4.23 that the DSS helped them gain a better view of how engineering design affects a business.

3) "The DSS shows that a system linked analysis improves system-level decisions". This is supported from viewing survey question number 4 where users state with a rating of 4.05 that the tool helps with system level decisions. However, with the outcome of the results shown in Figure 4.13, it shows that users did not, in practice, find a difference between the system where there was a true system link as opposed to only a partial system linkage, which was presented in the constrained DSS. This may be due to an overabundance of data which was given to users in the unconstrained test.

4) "Decision makers can see how small changes affect the system". Question 12 in the survey asked about small changes in the system, however many of the users were not able to satisfactorily answer this question and not much could be derived from it. Furthermore, users who tested with the unconstrained variant were not able to directly see what changes were made and could not answer this question very well. In the end, no conclusions were drawn from this question.

5) "The DSS improves the ability to make decisions". The was supported in questions 2 and 6 of the survey questions where users gave ratings of 3.98 and 4.18 to the tool helping them make more effective decisions. Furthermore, 91% of users who were not able to make a decision with the unprocessed data were able to make a decision with the System DSS as is shown in Figure 4.2. This shows that their ability to make a decision was increased greatly over the unprocessed data.

6) "The DSS creates a better view of engineering and business interactions than unprocessed data". This was supported as is demonstrated in Figure 4.1, where user's confidence was shown to be statistically higher with the System DSS as far as making a decision was concerned.

This is also shown in question 5 in the survey questions which states that the interactions between the two can be seen, which was rated at 4.18.

7) “The integrated data supports reaching better decisions than unprocessed data”. As shown in the survey question number 3, the users rated at 4.41 that the tool helped them find better solutions, which supports this hypothesis. However, since the answer to add the chair contained two correct answers, it was hard to make any conclusions beyond that the users felt that they had made a better decision.

8) “More choices can be analyzed in the DSS than with same amount of time using unprocessed data” In the survey, viewing questions 7 and 8, it is seen that users found that the tool saved time and helped them make more analyses quicker, which supports this hypothesis.

Many of the hypotheses were directly addressed by the survey questions. It is clear that the System DSS, regardless of the variant, was a better favored choice than using the unprocessed data for the analysis. The absence of variation between outcomes of the two test variants was unexpected however.

4.9 Further Information

Not included in the 44 testers was one of the employees of the sponsoring company who was able to use the tool and do analysis for himself. He remarked in the survey about whether or not to add the chair, “Based on the payback time, it does appear to be a good product to add to our line. We are currently in the process of adding a chair similar to the one in Troy’s program based on his recommendations.”

CHAPTER 5. CONCLUSION

5.1 Summary

DSSs have been developed and used in the past, however the effectiveness of integrating the DSS with other systems so that it better showed system effects has had little attention, specifically in the area of product design and business integration. The System DSS which was developed for this research was developed to see if a system view is truly more useful than just having unprocessed data or a non-System DSS. The DSS consisted of an integrated PDG and business DSS to show the effects of product design on the system through user testing. Testing was performed on the System DSS to see if it in fact increased the effectiveness of decision makers. Results confirmed that the DSS increases the effectiveness of decision maker decisions by helping them better understand the choices they were making over using the unprocessed data. However, the limitations on the constrained DSS did not hinder the users' ability to make confident decisions, nor was it shown in the survey that such was the case. Decision makers rated the tool quite well in all the areas that were questioned regardless of the test type. From this, it can be concluded that many of the hypotheses were correct and that the System DSS is in fact more useful. However, an interesting conclusion was also made that the two test variants showed no statistical difference on the decision maker's ability to make decisions.

5.2 Recommendation

Since this sort of tool was shown to be preferred by users in this testing scenario, the author considers the design and usage of a System DSS to be useful in industry. Furthermore, the more complex a system is and when decisions are repeated more than once, a tool such as the one in this research becomes even more beneficial. With designing a simpler product like a chair, the benefits are somewhat reduced since developing an entire PDG takes significant time and efforts relative to how long it takes to make a good design for a chair. However, in a system where the product being analyzed is affected by many factors that are hard to visualize (e.g. flash memory, military systems) a tool similar to the one developed in this research could be very beneficial because it will allow the designer to account for interactions that would not otherwise be able to be seen.

5.3 Limitations

There are certain limitations to the testing performed in this study. The first is that testers were generally college students from colleges in Utah Valley. This could bias the results because many of these people have not worked in a position where they had to analyze data to make decisions in a workplace setting, though giving them unprocessed data may have helped them understand to some degree what it is like. Lastly, the variants that were created had insufficient differences to alter the users testing outcomes. Among the variant differences, decision makers had less ability to see how small changes affected the system, but could still see the system as a whole, meaning that with further limitations in the constrained system, there could be different outcomes.

5.4 Future Work

There is a large amount of work that has been performed in the area of decision support systems which is evidenced by the many articles and journals entirely dedicated to the subject. More than simple DSSs, but the integration of systems into multi-disciplinary analysis tools could be further explored. Adding to this, standardizing decisions support system by creating an easy to use framework that can accept numerous types of equations to assist in the decision maker's ability to more efficiently make an interactive DSS is a research topic that could provide significant benefits in this area. Finally, the principles of visualization, optimization, and dynamic analysis are used in many DSSs and when these principles are applied to additional datasets the results could open up new avenues of data fusion and decision making techniques.

Other additions to this sort of tool could include Pareto frontiers on the Monte Carlo analysis. This could allow users to view only good designs rather than having to sift through the design space. These additions would enable improved solution definition, and reduce the time users spend analyzing dominated designs of which the decision maker may not be interested.

Furthermore, the product design generator has the ability to be optimized for minimum material conditions within design constraints. This would allow for a system that is completely optimizable through computer aided engineering techniques. Optimization that takes into consideration all systems could be of greater analytical benefit for identifying the global optimum across even more dimensions than included in the above research.

REFERENCES

[1] P. Masai. (2014) The quest of one piece flow. [Online]. Available: http://www.slideshare.net/InstitutLeanFrance/the-quest-of-onepieceflow-in-it-by-pierre-masai-toyota-motor-europe

[2] “Noisy Function.” [Online]. Available: http://ih.constantcontact.com/fs032/1102610363105/img/25.png?a=1102861224583

[3] Drive2016. (2016) Bath bench with back and arms. [Online]. Available: http://www.drivemedical.com/index.php/premium-series-shower-chairwith-back-and-arms-285.html

[4] M. Ginzberg and E. Stohr, “Decision support systems: Issues and Perspectives,” *Center for Digital Economy Research*, vol. 27, no. 82-12, 1982. [Online]. Available: http://papers.ssrn.com/sol3/papers.cfm?abstract{_}id=1290170

[5] P. G. Keen, “Decision support systems: The next decade,” *Decision Support Systems*, vol. 3, no. 3, pp. 253–265, 1987. [Online]. Available: http://linkinghub.elsevier.com/retrieve/pii/0167923687901801

[6] P. Todd and I. Benbasat, “Evaluating Effort , and of DSS , Impact Cognitive Incentives on Strategy Selection,” *Information Systems Research*, vol. 10, no. 4, pp. 356–374, 1999.

[7] A. X. Garg, N. K. J. Adhikari, J. Beyene, J. Sam, and R. B. Haynes, “Effects of Computerized Clinical Decision Support Systems on Practitioner Performance,” *JAMA: The Journal of . . .* , vol. 293, no. 10, pp. 1223–1238, 2005.

[8] J. M. Pearson and J. P. Shim, “An empirical investigation into DSS structures and environments,” *Decision Support Systems*, vol. 13, no. 2, pp. 141–158, 1995.

[9] D. Te’eni and M. J. Ginzberg, “Human-computer decision systems: The multiple roles of DSS,” *European Journal of Operational Research*, vol. 50, no. 2, pp. 127–139, 1991.

[10] J. Martins, *Multidisciplinary Design Optimization*.

[11] J. M. Ehrenfeld, F. Dexter, B. S. Rothman, B. S. Minton, D. Johnson, W. S. Sandberg, and R. H. Epstein, “Lack of utility of a decision support system to mitigate delays in admission from the operating room to the postanesthesia care unit,” *Anesthesia and Analgesia*, vol. 117, no. 6, pp. 1444–1452, 2013.

[12] M. Geurts, “Data problems in decision support systems,” *System Sciences, 1994. Proceedings of the Twenty-Seventh Hawaii International Conference on*, vol. 3, pp. 3–6, 1994.

[13] D. W. Bates, G. J. Kuperman, S. Wang, T. Gandhi, A. Kittler, L. Volk, C. Spurr, R. Khorasani, M. Tanasijevic, and B. Middleton, "Ten Commandments for Effective Clinical Decision Support : Making the Practice of Evidence-based Medicine a Reality," *Journal of American Medical Informatics Association*, vol. 10, no. 6, pp. 523–530, 2003.

[14] F. Lee, J. M. Teich, C. D. Spurr, and D. W. Bates, "Implementation of physician order entry: user satisfaction and self- reported usage patterns," *J Am Med Inform Assoc*, vol. 3, pp. 42–55, 1996.

[15] J. J. Jiang, G. Klein, C. L. Carr, G. Klein, and C. L. Carr, "Using and Attribute-Based DSS for User Customized Products Online: An Experimental Investigation," *MIS Quarterly*, vol. 26, no. 2, pp. 145–166, 2016.

[16] L. Niu, J. Lu, G. Zhang, and D. Wu, "FACETS: A cognitive business intelligence system," *Information Systems*, vol. 38, pp. 835–862, 2013.

[17] P. M. Sengue, *The Fifth Discipline*, 1st ed. New York: Doubleday, 1990.

[18] D. Arnott and G. Pervan, "Eight key issues for the decision support systems discipline," *Decision Support Systems*, vol. 44, no. 3, pp. 657–672, 2008.

[19] V. L. Sauter, "Intuitive Decsison Making: Combining advanced Intuitive analytical tools with human intuition increases insight into Decision-Making," *Communications of the ACM*, vol. 42, no. 6, pp. 109–115, 1999.

[20] H. G. Watson, *Business Systems Engineering*, 1st ed. New York: John Wiley and Sons, 1994.

[21] G. Ariav and M. J. Ginzberg, "DSS design: a systemic view of decision support," *Communications of the ACM*, vol. 28, no. 10, pp. 1045–1052, 1985.

[22] S. Y. Engine, "Systems Engineering for Better Engineering," no. December, 1995.

[23] A. Parkinson, R. Balling, and J. Hedengren, *Optimization Methods for Engineering Design*, Provo, 2013, no. November.

[24] J. K. Liker, *The Toyota Way*. McGraw-Hill Education, 2003.

[25] S. Helfenstein, O. Kaikova, O. Khriyenko, and V. Terziyan, "Emotional Business Intelligence," 2014.

[26] H. Ltifi, E. Ben Mohamed, and M. ben Ayed, "Interactive visual knowledge discovery from data-based temporal decision support system," *Information Visualization*, 2015. [Online]. Available: http://ivi.sagepub.com/lookup/doi/10.1177/1473871614567794

[27] J. Lu, L. Niu, and G. Zhang, "A situation retrieval model for cognitive decision support in digital business ecosystems," *IEEE Transactions on Industrial Electronics*, vol. 60, no. 3, pp. 1059–1069, 2013.

[28] C. Gomes da Silva, J. Figueira, J. a. Lisboa, and S. Barman, "An interactive decision support system for an aggregate production planning model based on multiple criteria mixed integer linear programming," *Omega*, vol. 34, pp. 167–177, 2006.

[29] S. I. Petersen, "Design quantification: design concept argumentation as related to product performance metrics," no. April, p. 342, 2009.

[30] M. E. Bare and M. E. Bare, "Structuring Emperical Methods for Reuse and Efficiency in Product Development Processes," 2006.

[31] T. W. Simpson, T. W. Simpson, S. Zahed, S. Zahed, J. R. Jiao, and J. R. Jiao, *Product Platform and Product Family Design*, T. Simpson, Ed., 2006.

[32] J. P. Shim, M. Warkentin, J. F. Courtney, and D. J. Power, "Past , present , and future of decision support technology," vol. 33, pp. 111–126, 2002.

[33] W. E. Pracht and J. F. Courtney, "The Effects of an Interactive Graphics-Based DSS to Support Problem Structuring." *Decision Sciences*, vol. 19, pp. 589–621, 1988. [Online]. Available: http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=4946780&lang=es&site=ehost-live

[34] T. Andersson and P. Värbrand, "Decision support tools for ambulance dispatch and relocation," *Journal of the Operational Research Society*, pp. 195–201, 2006.

[35] D. T. Ford, "Flood-Warning Decision-Support System for Sacramento, California," no. August, pp. 254–260, 2001.

[36] B. Schneiderman and C. Plaisant, *Designing the User Interface*, 5th ed. Boston: Addison Wesley, 2010.

[37] J. M. Young, "Nesting Automated Design Modules In An Interconnected Framework," *BYU*, 2005.

[38] M. Yamamoto, "The impact of product aesthetics on the evaluation of industrial products," *Journal of Product Innovation Management*, vol. 11, pp. 309–324, 1994.

[39] S. Institute., "Jmp statistical discovery software." 2014.

[40] S. c. Dassault Systems, "Solidworks," 2013.

[41] MATLAB, *version 8.4.0 (R2014b)*. Natick, Massachusetts: The MathWorks Inc., 2014.

[42] G. M. Roach, J. J. Cox, and C. D. Sorensen, "The product design generator: A system for producing design variants," *International Journal of Mass Customisation*, vol. 1, no. 1, pp. 83–106, 2005.

[43] MatWeb. Overview of materials for pvc, extruded. [Online]. Available: http://www.matweb.com/search/datasheettext.aspx?matguid=bb6e739c553d4a34b199f0185e92f6f7

[44] M. Kyrill and M. Thieme, *Activating the Innovation Potential of SME: The Bottom-Up Approach*, 2010.

[45] M. Y. Chen, "A hybrid ANFIS model for business failure prediction utilizing particle swarm optimization and subtractive clustering," *Information Sciences*, vol. 220, pp. 180–195, 2013. [Online]. Available: http://dx.doi.org/10.1016/j.ins.2011.09.013

[46] K.-P. Lin, P.-F. Pai, Y.-M. Lu, and P.-T. Chang, "Revenue forecasting using a least-squares support vector regression model in a fuzzy environment," *Information Sciences*, vol. 220, pp. 196–209, 2013. [Online]. Available: http://dx.doi.org/10.1016/j.ins.2011.09.003

[47] X.-s. Yang, S. Deb, and S. Fong, "Accelerated Particle Swarm Optimization and Support Vector Machine for Business Optimization and Applications arXiv : 1203 . 6577v1 [math . OC] 29 Mar 2012," pp. 1–12.

[48] F. Niedermann, S. Radeschütz, and B. Mitschang, "Deep business optimization: A platform for automated process optimization," *Proc. of ISSS and BPSC, ...*, pp. 168–180, 2010. [Online]. Available: http://subs.emis.de/LNI/Proceedings/Proceedings177/172.pdf

[49] D. Halsall and D. Price, "A dss approach to developing systems to support production planning and control in smaller companies," *International journal of production research*, vol. 37, no. 7, pp. 1645–1660, 1999.

[50] C. Gomes da Silva, J. Figueira, J. a. Lisboa, and S. Barman, "An interactive decision support system for an aggregate production planning model based on multiple criteria mixed integer linear programming," *Omega*, vol. 34, pp. 167–177, 2006.

[51] A. G. K. G. Peterson, Robert A, "The public's definition of small business," *Journal of Small Business Management*, vol. 24, no. 3, p. 63, 1986.

[52] J. Behrens and H. Ernst, "What keeps managers away from a losing course of action? go/stop decisions in new product development," *Journal of Product Innovation Management*, vol. 31, no. 2, pp. 361–374, 2014.

[53] R. Shephard and R. Fre, "The law of diminishing returns," in *Production Theory*, ser. Lecture Notes in Economics and Mathematical Systems, W. Eichhorn, R. Henn, O. Opitz, and R. Shephard, Eds. Springer Berlin Heidelberg, 1974, vol. 99, pp. 287–318. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-80864-7_17

[54] M. Wright, "Advertising Budget," no. 10565, 2008.

[55] J. W. Churchill, Neil C. Mullins, "How fast can your company afford to grow," *Harvard Business Review*, no. R0105K, 2001.

APPENDIX A. CODE

All code can be viewed by vising https://goo.gl/sPls9V. To copy the code for usage, use the links under the individual sections. If you have questions about the code, send me an email at TroySeletos@gmail.com

A.1 Solidworks Code

Code was used to run a macro in Solidworks to update the model and push certain data out to text. This code can be viewed online by visiting https://goo.gl/2g3YLD

A.2 Weight Equation

This is the equation generated by the neural network for calculating the weight of the chair. This equation can be seen in the JMP Code on page 65, line 4069. (Page 64 if in view-only mode)

A.3 Matlab Code

This is the code that contains all the equations for the business. This code is iterated through the fmincon optimizer to find the optimal values for the business. The code can be viewed online at https://goo.gl/XL6Gkl

A.4 JMP Code

The code contains all necessary information to reproduce the "unconstrained" test as talked about in the report. By manipulating the code slightly to hide the scatterplot, force the decision maker to move forward after making answers (and not being able to go back), and separating the product design DSS and business DSS onto separate tabs, the "constrained" test can be reproduced as well. The code can be found online at https://goo.gl/i76Yrj