Communicating Optimization Results

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ABSTRACT

With global supply chains becoming increasingly complex, leading companies are embracing optimization software tools to help them structure and coordinate their supply chains. With an array of choices available, many organizations opt for one of the numerous off-the-shelf products. Others choose instead to create their own bespoke optimization tools. While this custom approach affords greater versatility than a commercially available product, it also presents significant challenges to both the creators and users of the tool in terms of complexity. It can often be time-consuming and difficult for the users of the tool to understand and verify the results that are generated. If a decision-maker has difficulty understanding or trusting the output of a model, then the value of the tool is seriously diminished. This paper examines the challenges between the creators, or operational research engineers, and the end-users when deploying and executing complex optimization software in supply chain management. We examine the field of optimization modeling, communication methods involved, and relevant data visualization techniques. Then, we survey a group of users from our sponsoring company to gain insight to their experience using their tool. The general responses and associated crosstab analysis reveals that training and visualization are areas that have potential to improve the user's understanding of the tool, which in turn would lead to better communication between the end-users and the experts who build and maintain the tool. Finally, we present a section on current, cutting edge visualization techniques that can be adapted to influence the way a user visualizes the optimization results.

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1. INTRODUCTION

With global supply chains becoming increasingly complex, leading companies are embracing optimization software tools to help them structure and coordinate their supply chains. While many organizations choose off-the-shelf products, others, such as our sponsor, Company X, build their own bespoke optimization Solver tools to manage their specific needs. The purpose of the tool, whether off-the-shelf or custom built, is to fulfill demand while optimizing factory and inventory costs (raw materials, work-in-process, and finished goods) worldwide. With a multitude of sites and potentially thousands of products and customers stretched around the globe, companies recognize that these tools are vital to ensuring their competitiveness.

To build a bespoke optimization tool, companies typically employ a staff of operations research engineers (OREs) and software developers. OREs are extremely skilled in the application of optimization methods; some are found in universities and others are brought in from industry to blend experience with optimization modeling theory. Company X began the process of developing its own supply chain optimization tool in 2005. Prior to this endeavor, their supply chain planning was executed primarily through the use of spreadsheets. When it transitioned from spreadsheets to an optimization tool, Company X employed a prominent operations research expert from a leading university. After the OR expert formed his team of engineers and developers, an optimization tool was produced and deployed to the company's supply chain planners.

Figure 1 below further explores the dynamics associated with the introduction and deployment of bespoke optimization tools within large organizations. The diagram is intentionally simple and is included here to illustrate the key dynamics associated with organization optimization model use, namely adoption and desertion.

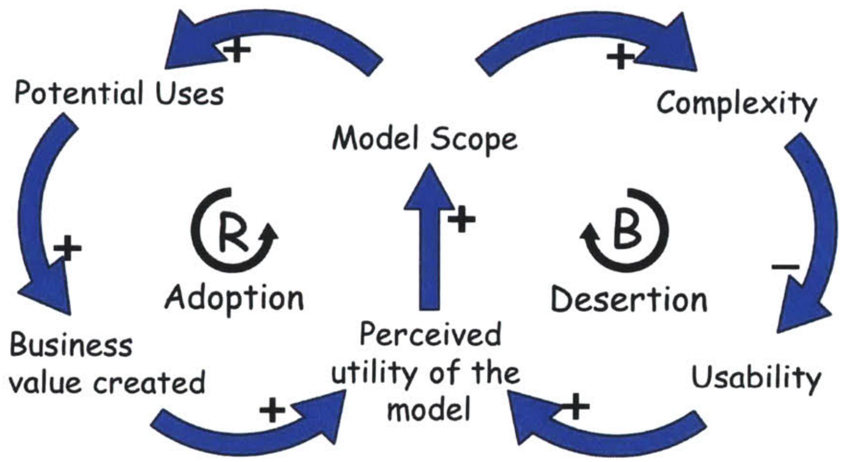

Figure 1 : Casual Loop Diagram

When companies deploy optimization models, they typically begin with a pilot project and a tightly focused model that is designed to address a very specific challenge. With this in mind, the above causal loop diagram essentially starts with the *"model scope"* parameter. Following counter-clockwise from the model scope, we see an arrow that is connected to the *"potential uses"* parameter. As the scope of the model expands over time, the amount of potential uses for the model also expands. Consequently, an increase in the potential uses of the model has a positive impact on the overall business value that the model creates. When the model usage becomes clearly associated with tangible business value, word-of-mouth quickly spreads among the constituent stakeholders in the company, leading to a larger fan-base of model advocates and resulting in an increase in the overall perceived utility of the model inside the company. These new converts soon evangelize the benefits of the model, which in turn leads to an increase in the model's scope. By returning to the model scope parameter, we have closed the first of the two loops reflected on the diagram. In this case, the loop is to the left and is labeled as the *"adoption"* loop. Using Systems Thinking nomenclature, we have just described a reinforcing loop that represents a virtuous cycle of model adoption within the organization.

With the inclusion of only the reinforcing loop, the diagram is missing a key element. In order to accurately convey the simple dynamics, we need to include a balancing loop. In this case, our balancing loop is to the right hand side, and is labeled as the *"desertion loop,"* and reflects the counter scenario to model adoption. Following clockwise from the model scope, we see an arrow that is connected to the *"complexity"* parameter. This indicates that as model scope increases, so too does the overall complexity of the model. As the complexity of the model increases, it leads to a reduction in the model's overall usability. When the usability of the model diminishes, negative word-of-mouth ensues leading to a reduction in the perceived utility of the model. As the perceived utility of the tool is reduced, the credence that managers place on the tool is lessened and over time the model's scope will be decreased. By returning to the model scope parameter, we have now closed the balancing *"desertion"* loop.

These two counterbalancing conditions reflect a dichotomy that must be carefully managed. The initial wave of enthusiasm that accompanies the introduction of a new and useful tool is soon forgotten if the complexity of the tool reaches the level at which it hinders the user's ability to derive meaningful results.

In general, Company X, a semiconductor chip maker, has groups of decentralized production, assembly, and testing planners placed at sites all over the world. In total, there are around 60 planners and 20 sites across their global supply chain. Planners use the optimization tools created by the OREs to build their work plan on a monthly basis. Their work plan consists of how many wafers, which is the raw material for semiconductors, to fabricate, die, assemble, or test for an associated time period. Accomplishing this task requires that the planners possess an adequate understanding of the tool. If they do not understand the tool's results, and why those results occurred, then the perceived usefulness of the tool within the organization will be severely diminished.

Due to the inherent complexity and the vast amount of data that it handles, Company X's optimization tool had to be separated into various smaller applications that were tailored to each site's specific function. Starting at the semiconductor's raw material, the wafer, the first tool used is the fabrication solver, which optimizes the number of wafer production starts across the globe at each site. Based on a six week lead time from fabrication to customer, the model incorporates information from many different areas to optimize the company's global production capacity. This tool, called the Solver, is used by 38 of the planners. Due to time constraints and its scalability, we focused our study on this tool. Thus, you will see the term Solver used in almost all of our writing that pertains to Company X's optimization model.

1.1. The Nature of the Problem

Planners are typically employed after completing a period of undergraduate study in a related discipline. While the OREs who created the tools are experts in the creation of optimization models, the planners are focused on supporting the plant managers with optimal production numbers. Planners are not typically familiar with the inner workings of the Solver application. For example, when using the Solver, the only decision a planner needs to consider is what priority to choose. The priority settings, which can be 1, 2, or 3, allow the planner to place emphasis on the type of wafer to produce during the month. A number one represents the highest priority and a three is the lowest. The Solver incorporates the inputted priorities when optimizing the wafer starts.

After the planner has set the wafer priorities, the Solver tool is run. After the run has completed the planner views, interprets, and executes the results at his or her site. Should anything out of the ordinary happen during the solve run, or if the planners have any questions about the results, planners will initially speak with a senior planner within their group. The senior planner will work with them to answer their questions or help them address the issue. If this approach does not address the issue, the senior planner escalates the matter to the operations research engineers.

This process lies at the heart of the problem that we are investigating. Senior planners, called super-users, will work with the OREs to conduct root cause analysis on the issue with the Solver tool's results. The escalation process starts with an electronic issue or remedy ticket, which is called a POOL ticket at Company X, and involves phone calls, emails, and instant messaging to work through the issue.

To complete the root cause analysis, OREs use advanced techniques and knowledge to decipher what happened within the tool, and why it found the result that it did. To put the complexity of the tool in perspective, we observed one instance of the Solver which had approximately 1.2 million decision variables and 1.6 million constraints to factor in while calculating the outputs. The OREs are tasked with determining where the problem happened within this complex structure. After the OREs have found the answer, they need to explain it to the users, who in turn need to be able to understand what is being explained to them. A communication barrier ensues as the highly specialized OREs attempt to explain the nonintuitive results to the planners. OREs struggle with the explanation as the concepts are very complicated and the planners don't always grasp the broader perspective of the optimal results since they often focus on the impact of the results to their site. Planners frequently have difficulty understanding the complicated technical jargon that is used by the OREs when discussing optimization models, making it difficult to receive the information and either disseminate or execute at their site.

Adding to the problem is that the Solver requires version updates every 18-24 months to reflect the evolving needs of Company X's supply chain. Planners receive training on the version updates and gradually adjust to the tool's updated interface. Training is usually in the form of PowerPoint slides that explain user interface updates or instruction by the senior planner at the site. Again, OREs must transfer the information to the planning community at a complexity level appropriate to their role. This is a difficult challenge at the Company X, and a common barrier at many companies using optimization modeling for production planning.

With this communication barrier in mind, we are studying how the experts effectively manage deploying complex optimization tools in a decentralized planning environment. Our approach includes interviews, an extensive literature review, and a survey of the users of the tool. Incorporating the results, we aim to provide Company X with ways to improve their connection between the OREs and planners. Since the problem is applicable across many industries and disciplines, the results will not only be applicable to Company X, but can be used by other companies to manage their communication between experts and business users of complex optimization tools.

1.2. Research Objective

By exploring the dynamics of the communication barrier between Company X's supply chain experts and its planners, we have set the following research objectives:

- Produce insightful thoughts on new areas for improvement by conducting detailed interviews and surveys.
- Develop new communication methods for Company X to use when approaching root cause analysis.
- Introduce training ideas to teach planners how to effectively use priorities when running the Company X Solver.
- Identify and recommend innovative approaches to visualizing the results of the Company X Solver.

Accomplishing these objectives will provide Company X with different avenues to attack the communication problem. One accomplished objective will likely not be a panacea, but we believe a combination of the four objectives will provide a foundation for an industry-leading solution to a common problem.

2. LITERATURE REVIEW

We conducted a review of the material related to communicating and visualizing complex optimization models. We found the majority of the sources focus on using visualization to assist in solving complex optimization problems. Our topic is focused on the visualization and communication of the optimization results after the solve process has completed, so many of these sources were not relevant. Independently, there are plenty of sources available on optimization modeling, communication, and visualization of data, but very few focus on combinations of the topics.

This chapter begins with a basic introduction to optimization modeling; then, we present relevant material for communication and visualization.

2.1. Optimization Modeling

We begin the literature review process by first developing an understanding of what is meant by "Optimization Modeling." Carraway (2010) defines an optimization model as "a model that uses mathematical programming to find an optimal quantity." According to Sterman (1991), optimization models represent a special category of computer models, and he describes them as "normative or prescriptive" (i.e. conveying the single "best" solution). Sterman then contrasts them with simulation models whose purpose is descriptive as opposed to prescriptive and therefore to accurately reflect the behavior of a real system. The component parts of an optimization model are generally an objective function, many decision variables and many constraints. After these components have been defined, the model is then run to provide the optimal solution for the given constraints. Sterman (1991) illustrates the practical use of a simple optimization model by referring to a hypothetical example of a traveling salesman who needs to travel to a number of cities in the mathematically shortest possible time.

Carraway (2010) further divides optimization models into three categories: non-linear, linear and integer programming.

Bertsekas (1999) defines non-linear programming as "the process of solving a system of equalities and inequalities, collectively termed constraints, over a set of unknown real variables, along with an objective function to be maximized or minimized, where some of the constraints or the objective functions are nonlinear." Non-linear optimizations are generally solved through the use of calculus, and are typically more difficult to solve than equivalently structured linear optimizations (Carraway 2010).

Linear programming is similar to non-linear programming, except that the constraints and the objective function are all linear. While it is possible to solve linear programming models using non-linear techniques, the simplex method is far more efficient and more commonly used (Carraway 2010). The simplex method was introduced by George Dantzig in 1947 as an iterative approach that solves a series of linear equations as it performs each step, and stops when either the optimum is reached, or the solution proves infeasible.

Integer programming is similar to both linear and non-linear programming, except that some or all of the constraints and the objective function are set to be integers. The most common approach for solving integer programming models is called "Branch and Bound" (Carraway, 2010), (A. H. Land and A. G. Doig, 1960). The Branch and Bound method is predicated on the systematic enumeration of all candidate solutions, where large subsets of fruitless candidates are discarded in bulk, through the use of upper and lower estimated bounds of the quantity being optimized.

Carraway (2010) presents three commonly encountered business decisions to provide context for the utility of optimization modeling techniques. They are optimal order quantity, product mix planning, and facility location. By referring to these differing cases, Carraway illustrates that optimization models are prevalent across different functions of the industry.

Sterman (1991) contrasted the benefits and drawbacks that computer models offer over mental models. Factors in favor of the use of computer models include that the results are explicit and open for all to critique and review, they are logical, and that they are able to interrelate many factors simultaneously. Sterman also indicates several potential flaws to the use of computer models. These include:

Complexity: Models are often so complicated that the user has no confidence in the consistency or correctness of the results that have been generated.

Incompleteness: Models are not designed to deal with factors that are difficult to model or were left because they are outside of the expertise of the specialists who built the model.

Opaqueness: Models are often so complicated that nobody can examine their assumptions; to the users they are black-boxes.

Carraway (2010) expands upon the theme of incompleteness when he indicates an optimization model's inability to handle uncertainty in the decision-making environment. It is important to note that neither author implies the drawbacks are reasons to not use optimization models; rather they caution that the models are not a panacea.

2.2. Communication of Optimization Modeling

From the user's perspective, models generate two forms of communication that are important to consider: communication with the model and communication with the model's developers. Little (1970) expressed that models should contain simple communication methods so the user feels comfortable incorporating outputs into his or her decision. Internally, the model must be robust, covering all parameters involved in a conclusive output. Externally, the language and inputs presented to the user should fit his or her operational understanding of optimization modeling.

Little (1970) continues to say that exposing parameters and constant numbers with little relevance to the user's decision is excessive and that it is best to keep the interface as simple and understandable as possible. However, displaying reference values for comparison of inputs and outputs will assist the user in decision-making (Little, 1970). Users can interpret how past inputs affected outputs critical to their system by viewing these reference values.

According to Little, the model's runtime is an important factor. For effective communication, models should produce timely outputs and allow the user to easily change inputs (Little, 1970). Users executing the model daily or weekly are negatively affected by models that run for long periods of time before producing the output. However, users interfacing with the model on an annual basis, or even quarterly, do not require outputs as quickly (Little, 1970).

Day and Kovacs (1996) explain the idea of an "intermediary" or someone who interprets a complex model and bridges gaps between the users and their source of information, the model. Usually an expert in the field and likely one of the developers of the model, the intermediary must match his or her communication medium and explanation detail to the user's level of understanding. Otherwise, a useful, yet complicated model quickly becomes useless due to ineffective communication from the intermediary.

Unless co-located, intermediaries and users commonly communicate by some form of electronic message (Day & Kovacs, 1996). Electronic interaction could be in the form of e-mail, instant messaging, or forum-based. Depending on the level of the user and his or her personality, electronic communication may not be the best approach. It can lead to breakdowns and misunderstandings. Electronic communication places a limit on the user's understanding, affects the tone of the conversation, and creates misperceptions about an intermediaries' personality (Day & Kovacs, 1996).

Little (1970) explored another aspect of the communication between developers and users. He referenced two prior works, Mathes (1969) and Pounds (1969), while explaining the different approaches that managers and scientists use when faced with a problem. Managers want action and results, whereas scientists need to learn all about the topic at hand. In the end, managers will take action but may never consider all the facts of the problem, while scientists may never act, but will understand everything about the issue. With this in mind, developers of the model can enhance its use by building ways for the model to highlight differences between observed and intended results (Little, 1970). Users or managers should be able to see where they can make decisions due to aberrations in expected results so that they can adjust the results in a timely manner. A developer or scientist would like to learn about why the model chose that output, independent of the time incurred, while users are more concerned with fixing the result in an efficient manner. According to Little (1970), creators should use this difference in problem-solving approach when developing the model.

2.3. Data Visualization

While the usefulness of optimization modeling has been well documented and has led to its adoption across a wide range of applications, the complexity and communication challenges pose a difficulty for many organizations. Data visualization techniques have been playing an increasingly prominent role in the conveyance of complicated optimization model results.

Visualization techniques leverage interactive computer graphics to provide clearer insight into complicated models than traditional data-driven techniques.

Visualization relies on cognitive psychology and graphic design to provide theoretical and empirical guidance (Jones, 1996). Jones adds that there are no hard and fast rules when it comes to conveying optimization results graphically. He also writes at length about the different formats that can be employed to represent optimization results visually; after reviewing the work of Greenburg and Murphy, Jones concluded that no one approach would suit all applications. Jones instead suggests that combinations of different formats tailored to particular users and tasks are most likely to be successful. Some of the approaches mentioned by Jones included animated sensitivity analysis and dynamic queries.

When the human brain performs the task of visual perception, its purpose is to filter out only the pertinent information, so that effective and efficient decisions can be made (Conway, 2012). This data processing action performed by our brains is so well developed that it occurs subconsciously. Conway goes on to state that different regions of a human's visual field are prioritized differently by the brain. He expands upon this by pointing out that the act of reading text is actually a very complex process that begins with the reader scanning the text using the fovea region (a small depression in the retina where vision is most acute) of his or her eye. The brain then processes this information into something pertinent and usable. Conway points out that the human visual system is actually a collection of several sub-systems, each of which has a specific task. For example, one subsystem is dedicated to color perception, one to form and another to the perception of motion and depth. In his work with "information dashboard design," Stephen Few (2006) also investigates human data processing, and applies it to data visualization. Few points out that monitoring is *"most efficiently done with our eyes,"* pointing out that human eyes possess seventy percent of the sense receptors that we have in our bodies. Few's work is examined in more detail toward the end of this literature review.

Alberto Cairo (2013) presents the view that visualization should be "seen as a technology." He goes on to justify this assertion by indicating that technologies exist to achieve specific goals as well as enhance and extend ourselves, and that we use visualization techniques for the same reasons. Cairo goes on to acknowledge that data visualization is an emerging discipline that brings together a variety of fields as diverse as cartography, statistics, graphic-design, journalism, and computer science. If data visualization is a technology, then it must always be conducted with a purpose. Cairo recommends that a viewer ask the following questions when examining a piece of visually presented data:

- "What does the designer want me to do with the graphic?"
- "What shape should my data have?"

By examining these aspects, the data-presenter can reduce the likelihood of the data-consumer reaching erroneous conclusions. Cairo illustrates this point by mentioning the dangers of comparing datasets in absolute terms, for example, violent crime statistics in Detroit with those in a town in rural New York State. Since Detroit has a comparatively large population, it would be inaccurate to use an absolute variable such as total number of victims. Instead, it would be far more accurate to use a derived statistic instead, such as victims per 100,000 people (Cairo 2013). Cairo presents this information to illustrate that there are often multiple ways to convey information visually, and that the goal of the presenter should always be to think first about the types of questions that the reader needs to have answered by the graphic. When making presentation decisions, substance should be prioritized over style and when choosing the form of the presentation it should always be with a functional purpose in mind. Cairo acknowledges that appropriate graphic form selection is difficult, and that while no absolute rules exist, it is good design practice to first try and understand how the users are most likely to leverage the tool.

In his article describing how the Procter & Gamble Company conveys information to decision-makers, Harvard Business School's Tom Davenport argues that common platforms and approaches for data visualization are more important than the creativeness of the tool itself (Davenport, 2013). He goes on to explain that by establishing a common *"visual language for data,"* managers can dramatically expand the scope for data driven decision-making within their companies. Instead of simply pursuing the latest, "cool" new visualization tools, Davenport advocates the pragmatic use of data visualization to help senior managers quickly understand their businesses, so they can make better and more informed decisions.

In his book, *"The visual display of quantitative information,"* Edward Tufte shares significant insight on how data practitioners should display their findings in visual form to facilitate ease of interpretation and analysis. Tufte introduces the concepts of *"graphical integrity," "data-ink ratio," "data density," "chart-junk," and "small multiples"* (Tufte, 1983).

"Graphical integrity" refers to the need for visual representations to accurately convey the data that they represent. Tufte demonstrates this through a variety of graphs that exaggerate or distort the data being presented. He then presents a calculation he refers to as the "lie factor," which comes from the ratio of the effect shown in the graphic and the effect shown in the data. In the ideal case, these values equal one-another and the "lie factor" is equal to one. However, should the "lie factor" be greater than or less than one then the graph has exaggerated or underestimated the effect respectively (Tufte, 1983).

The term *"Data-ink ratio"* describes the relative amount of ink in a graphic that is used to convey data. According to Tufte, data graphic creators should aim to maximize the amount of the ink that is used in the graphic for data conveyance purposes. He then presents a calculation he refers to as the "data-ink ratio," which equals one minus the percentage of the ink in the graphic that is not used to convey data. Therefore, by this measure, the closer the "data-ink ratio" is to one, the better the graphic. Later, Tufte uses the term *"data density"* to refer to the amount of the overall visual display that actually conveys data. He advocates the use of higher data density in graphical displays (Tufte, 1983).

The term "Chart-junk" is used by Tufte to describe the elements in data display graphics that are not needed in order to understand the data that is being presented. He then proceeds to criticize the tendency of graphical designers to overuse visual effects when presenting data in chart form. Overuse of display features such as 3D can lead to an accidental distortion of the information being presented. By categorizing visual elements that are not key to data conveyance as chart-junk, Tufte aims to minimize its usage (Tufte, 1983).

Another technique that Tufte mentions is the use of *"small multiples."* This is a technique where a series of small, similar charts are conveyed side-by-side in a larger graphical display. Representing the data in this manner allows for the layering of information and for comparisons to be quickly and easily made between the different elements of data that are being presented (Tufte, 1983).

Drawing upon Edward Tufte's insights to displaying quantitative information, Stephen Few expands Tufte's work to the area of information dashboard design. Few points out that while significant advances have been made fields such as Data-Warehousing (DW) and Business

Intelligence (BI), relatively little progress has been made regarding our ability to effectively use that data. He goes on to implore BI vendors to focus on "engaging interaction with human perception and intelligence," and suggests they do this by "building interfaces, visual displays, and methods of interaction that fit seamlessly with human ability" (Few, 2006).

To emphasize this point, Few highlights that while the use of computerized *"dashboards"* to convey visually represented information is relatively common in industry, most of these efforts are ineffective at presenting information in a way that is simple to understand at a glance. He attributes this to a failure of communication caused by inadequate focus on design (Few, 2006). In his article entitled "Dashboard Confusion," that appeared in the March 20, 2004 issue of *Intelligent Enterprise* magazine, Few included the following definition of the term "dashboard":

"A dashboard is a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance" (Few, 2004).

Few emphasizes that the purpose of a dashboard is to communicate information and that it does not exist simply for show. Few originally stated "13 common mistakes in dashboard design" (Few, 2006), but subsequently shortened this list to the most prevalent in "6 common mistakes in dashboard design." The 6 mistakes are listed below (Few, 2012):

1) Exceeding the boundaries of a single screen.
2) Supplying inadequate context for the data.
3) Choosing inappropriate display media.
4) Ineffectively highlighting what's important.
5) Cluttering it with useless decoration.

6) Misusing or overusing color.

Few advocates for *"eloquence through simplicity,"* firmly believing that less is more when it comes to data visualization. He goes on to describe a process called *"visual monitoring,"* which refers to a sequence of steps that should be factored into the design of any dashboard. During this process, a user should be able to visually scan the dashboard, understand what he or she is seeing and be able to readily identify which aspects warrant further investigation. The user then examines those areas in more detail to determine if any action is necessary. Finally, should the user require additional "supporting detail" to aid their decision making, they should be able to easily and intuitively access this additional detail from within the dashboard itself. Few also suggests that where appropriate, the dashboard should facilitate automated responses and he gives the example of the system automatically generating alerts to system experts whose action may be necessary.

He goes on to emphasize the importance of getting the *"visual orientation"* of dashboards right. Since information displayed in this manner is intended to be quickly understood, it necessarily means that a high *"speed of perception"* is required when viewing this content. *"Speed of perception"* can be enhanced through the use of effective graphical display techniques. Few then contrasts the relatively slow, serial process of reading text with the far quicker, parallel process of interpreting well-structured data graphics (Few, 2006).

At the time of writing, there is a myriad of available tools that can be leveraged for information visualization. We examine these tools in further detail in the observations section, and we also broadly classify them into four main categories, *"Libraries & API's," "Frameworks & Communities," "Visual & interactive data analysis tools,"* and *"Mapping & planning visualization tools."* With the pace of innovation in the software industry, the frameworks and tools available from vendors will evolve and adapt over time. However, fundamental design principles such as "eloquence through simplicity" (Few, 2006), maximizing the "data-ink ratio," avoiding "chart junk," increasing "data density," and layering information (Tufte, 1983) are less likely to change; although, they may well be expanded upon as new communication mechanisms and technologies come to the fore.

3. RESEARCH METHODS

We began our research by conducting initial interviews at our sponsor company's supply chain optimization headquarters. Next, we conducted an extensive literature review and built smaller, representative models for our own understanding. Finally, we conducted a survey of users followed by closing interviews. Combining our interviews, education, and survey findings, we developed the key insights and observations that form the foundation of this thesis.

3.1. Initial Interviews

At the beginning of this study, we met with the team of operations research engineers that created Company X's optimization model. We spent two days at their location, learning about the evolution of the model, how it is deployed at Company X, and the myriad of mathematical layers that underpin its outputs. Though a large part of the interviews was spent learning about the how the model works, we also spent time reviewing the processes between experts and the users of the model (Anonymous ORE, 2012).

3.2. Optimization Modeling Education

After reviewing the material gained from the experts at Company X and reflecting on their answers to our questions, we proceeded with an extensive review of optimization modeling. We also formed our own foundation of optimization modeling through research and building of our own simplified models for educational purposes. Combining the literature review with our own models proved to be an insightful learning approach that helped us understand how quickly the model's outputs can grow in complexity. We started our models with the simple case of one product and one machine that had a known demand over the course of one year. We found the optimal solution through minimizing costs, given the inputs assumed. In our second model, we introduced TAKT time (the maximum time per unit allowed to produce a product in order to meet demand) to the machines and another product to the scenario. In our final models, we optimized multi-product, multi-machine scenarios. This lengthy endeavor was critical to our understanding of how quickly the tool can become too complex for the average user to understand why a result occurred.

3.3. Literature Review Approach

Next, we reviewed literature on relevant topics such as communication, data visualization, and cognitive approaches to problems. These topics provided us with information that led to the development of a survey that was used to ascertain the user's thoughts on the model. Further, it helped us develop potential solutions for Company X's experts. Also, when researching current data visualization techniques, we were able review the current software.

3.4. Survey of Users

After completing our literature review, we surveyed the users with the questions listed in Exhibit 1. These questions were developed with the following themes from our literature review: Understanding the Company X Supply Chain, Complexity, Effectiveness, Training and Experience, Visualization, and Communication. Each question was designed to attain knowledge on how the users interact with the tool, the training they have received, how effective the tool is, and how the experts can improve the tool or its processes. Also, we introduced open comment questions at the end of the survey to allow users to explain anything not covered previously. Figure 2 below depicts an example of two of the sections, Effectiveness and Visualization. Figure 3 depicts the optional comment and contact information questions.

7. Please rate the following questions on Effectiveness.

	strongly disagree	disagree	neither disagree nor agree	agree	strongly agree	N/A
The Solver make my job easier.	○	○	○	○	○	○
I am not comfortable with the accuracy of the solver's outputs.	○	○	○	○	○	○
If I have a question about the outputs/results, it is difficult to get an answer.	○	○	○	○	○	○
I am encouraged to submit suggestions for improvement regarding the Solver.	○	○	○	○	○	○

8. Please rate the following questions on Visualization.

	strongly disagree	disagree	neither disagree nor agree	agree	strongly agree	N/A
The solver displays only necessary information for my role as a planner.	○	○	○	○	○	○
The outputs/results of the solver are not displayed effectively.	○	○	○	○	○	○

Figure 2 : Sample Survey Questions

10. (Optional) What, if any, are your challenges with the Solver?

11. (Optional) If you have any comments regarding the Solver, please add them below.

12. (Optional) We would like to contact Solver users for a brief follow-up phone interview. If you can assist with this request, please fill out the fields below.

Name:

Job Title:

Email address:

Figure 3 : Sample Open Text Survey Questions

After developing the survey, we used a sample of users, two super-users with extensive experience, to ensure our questions were focused and explained correctly. We also had them take the survey to understand how long it might take and what the results would look like. Pre-examining the results allowed us to setup our questions in the best manner for the research. Finally, we administered the survey by emailing 38 users of the Solver.

4. DATA ANALYSIS

Of the 38 eligible planners, we received 26 responses, yielding a 68% response rate. First, we will present the general and crosstab survey data analysis. Then, we will provide further qualitative analysis from information received during interviews.

4.1. Survey Results

Questions 1-3 in Figures 4-6 were designed to develop the background of the users. Below, Figure 4 reveals that over 60% of the users have at least one year with the Solver. The takeaway is that we have an experienced group of users that should provide for better data and analysis.

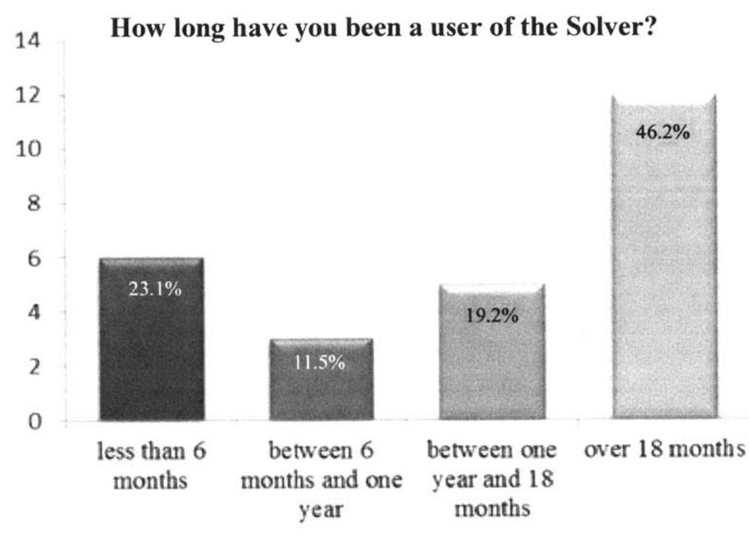

Figure 4 : Question 1 Results (Background Information)

Below, Figure 5 reveals the average time spent per week on the Solver. Surprisingly, the majority of the users spend very little time with the Solver, given its importance in planning the overall capacity for the company. Nearly 70% of the planners use the tool less than five hours per week.

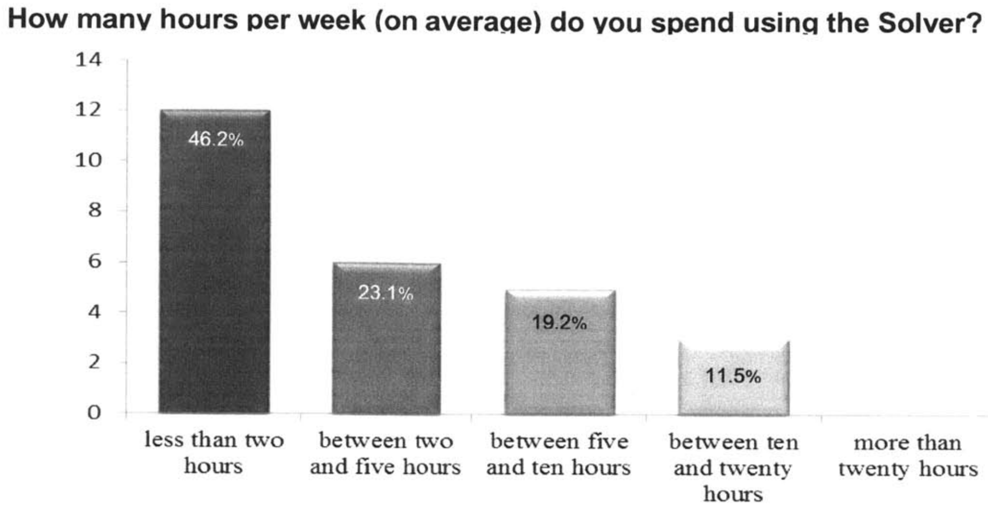

Figure 5 : Question 2 Results (Background Information)

Figure 6 helped us understand at what level the users perceived their understanding of Company X's supply chain and their location's role within that context. We are curious whether users feel that they can see the big picture when using the solver. Looking at the data, overwhelmingly, planners agree that they understand the supply chain and more importantly, they strongly agree that they understand their location's role. Only one user, or 3.8%, indicated that they do not understand Company X's supply chain, but they also responded that they understand their location's role.

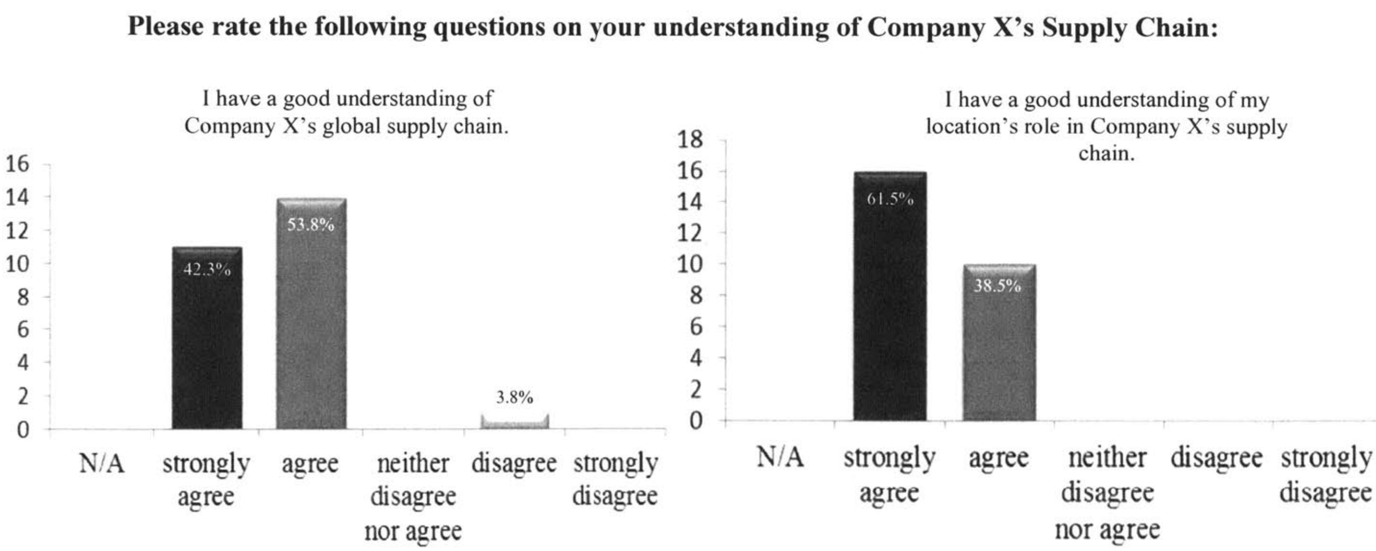

Figure 6 : Question 3 Results (Background Information)

4.1.1. User Training

After collecting general background information, we now focus on the topics that we introduced in the Literature Review and Methods sections. First, we asked questions about training received as a user. Appropriate training and experience with the Solver are catalysts for increasing communication effectiveness. Figure 7 asked when the users last received training. Almost 70% of the users received training within the last year. Only one user indicated that they never received training, while 27% were trained over one year ago. The results are positive overall, but ideally you want everyone to have completed initial training before using the solver. Furthermore, with an increasingly complex model, maintaining a minimum of annual training could be a realistic goal.

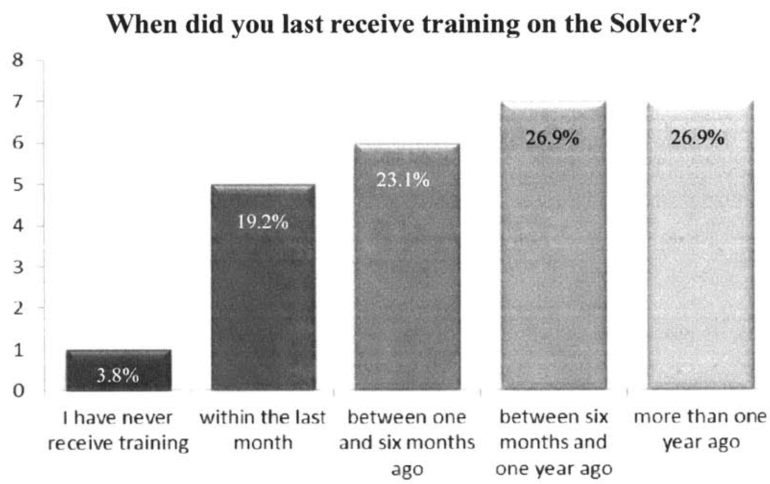

Figure 7 : Question 4 Results (Training Background)

The following questions about training and experience asked the user about adequacy of training and preference for additional instruction or experience. Interestingly, almost 70% believe that the training was adequate, while 85% believe that additional training and experience would be helpful. Given that 15% disagree with the training adequacy and 3.8% strongly disagree, while the majority wants more training and experience, this is an opportunity for improvement.

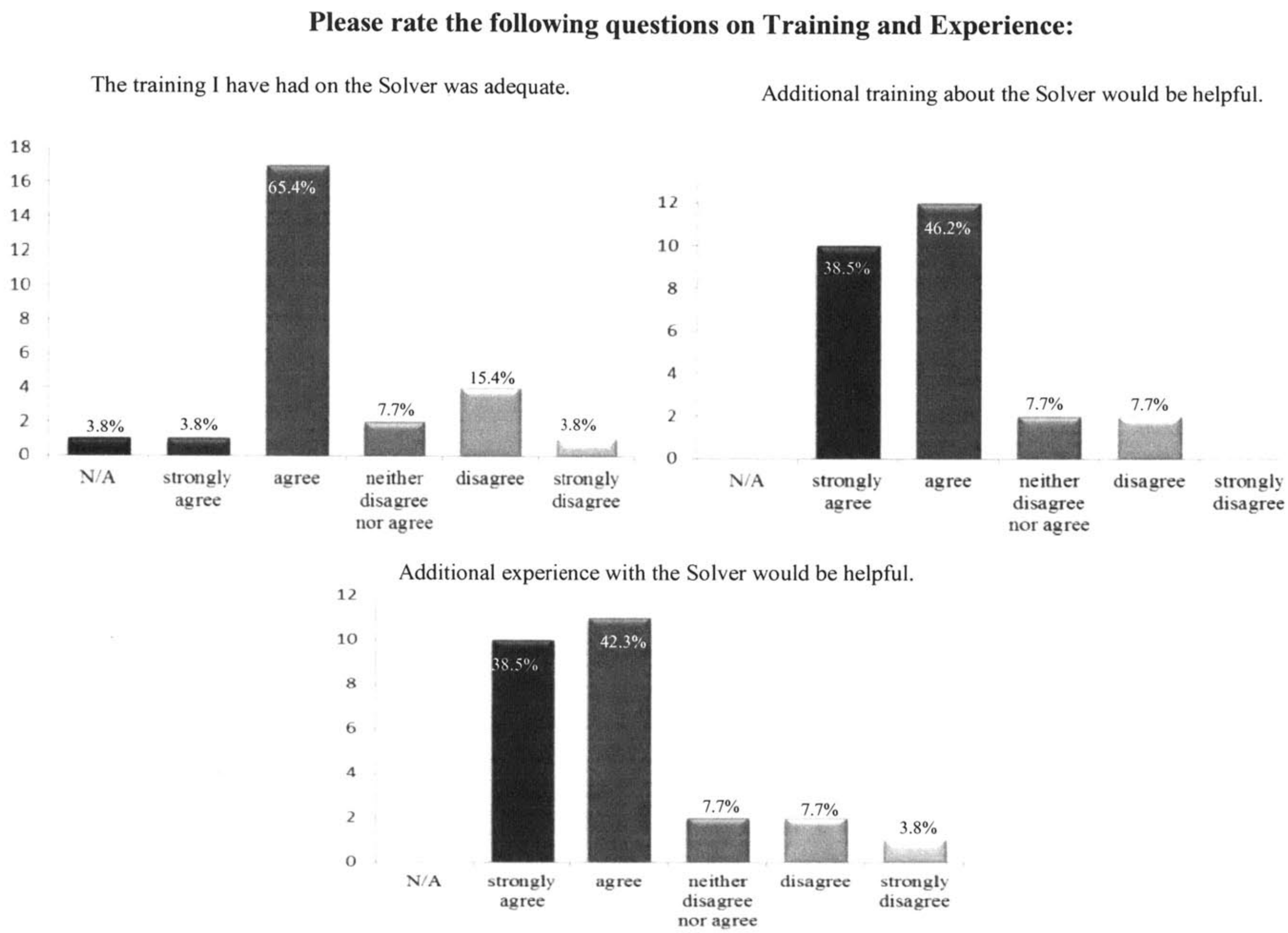

Figure 8 : Question 5 Results (Training)

4.1.2. Model Complexity

The next topic, complexity, asked four questions about how users perceived the simplicity of the model, its inputs and outputs, and how priority inputs affected the solver's outcome. 45% of the users expressed that the Solver was not simple to use, while only 31% felt that it is simple. 7.7% strongly agreed that it was not simple vs. 3.8% that felt it was. Next, 50% of users indicated that the solver's inputs are difficult to understand (11.5% strongly agreed vs. 0% strongly disagreed). While the first two questions revealed complexity in the tool, the third question about priority understanding indicates that over half of users are comfortable with how changes in priorities affect the Solver's outcome. The final question on outputs shows that users are equally split three ways: users agree that outputs are difficult to understand, neither disagree nor agree, and disagree that outputs are difficult. From this section, we see that there are opportunities to reduce the complexity of the inputs and outputs with respect to the user. However, we were pleasantly surprised that many users are comfortable with the effects of changing priorities.

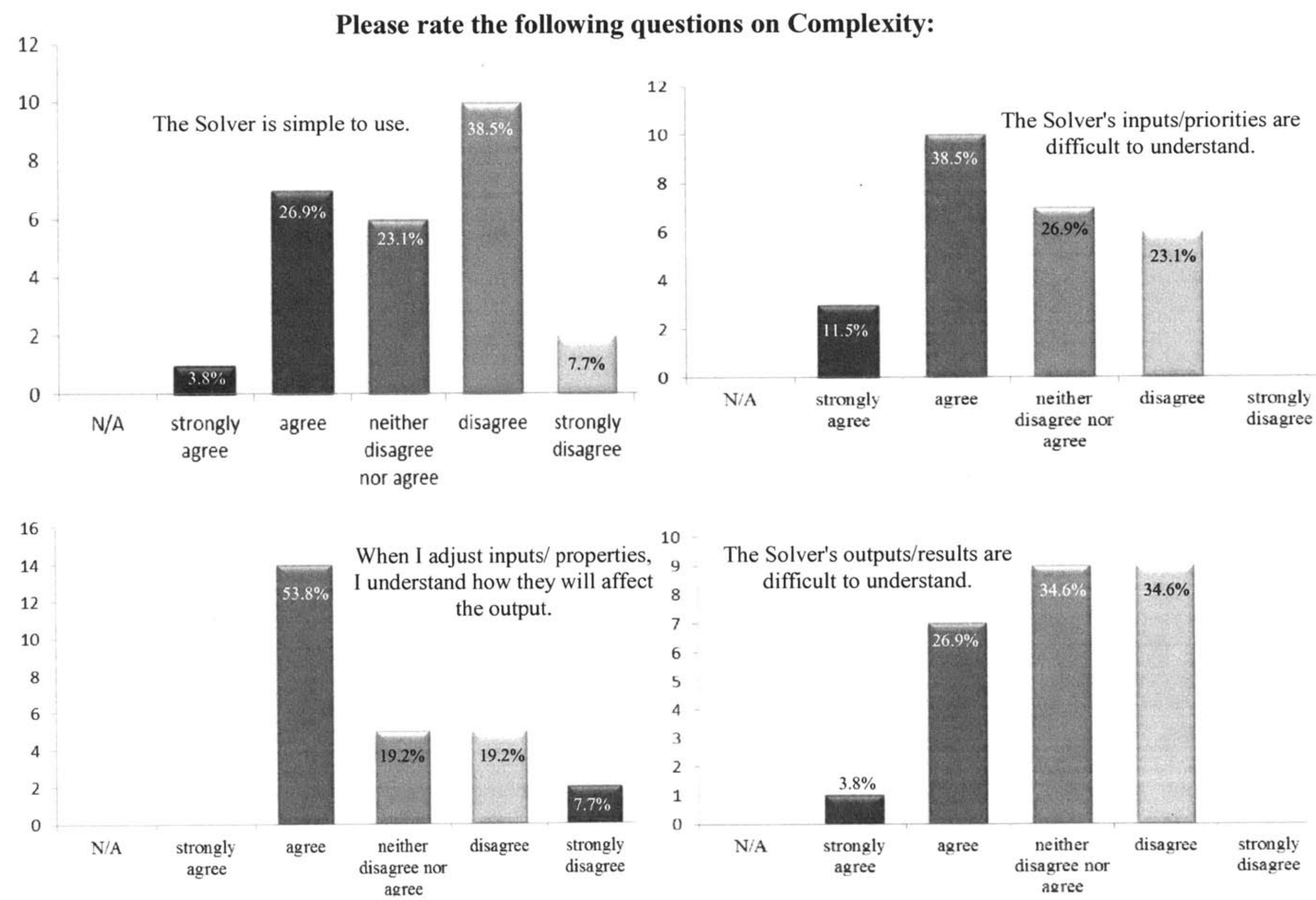

Figure 9 : Question 6 Results (Complexity)

4.1.3. Model Effectiveness

Effectiveness is the next topic that we introduced. Four questions were used to analyze the user's perception of Solver's effectiveness. The first question asked if the Solver makes the planner's job easier. While a few users were neutral, they overwhelmingly showed that the tool improves their job. Next, we looked at the how the users perceived the accuracy of the outputs. The answers to this question provide insight into the level of trust between the user and the model. Again, almost 70% indicated they are comfortable with the outputs. Only 15.4% were uncomfortable with the tool's accuracy. The trust is much higher than we expected. Our third and fourth questions were meant to gauge the user's perception of the how effective the remedy and process improvement systems function. Both sets of answers reveal that the majority feels the remedy system is working (over 50%) and process improvements are encouraged (over 45%). Our takeaway from this section is that the majority of planners are comfortable with the accuracy and processes surrounding the Solver.

Please rate the following questions on Effectiveness:

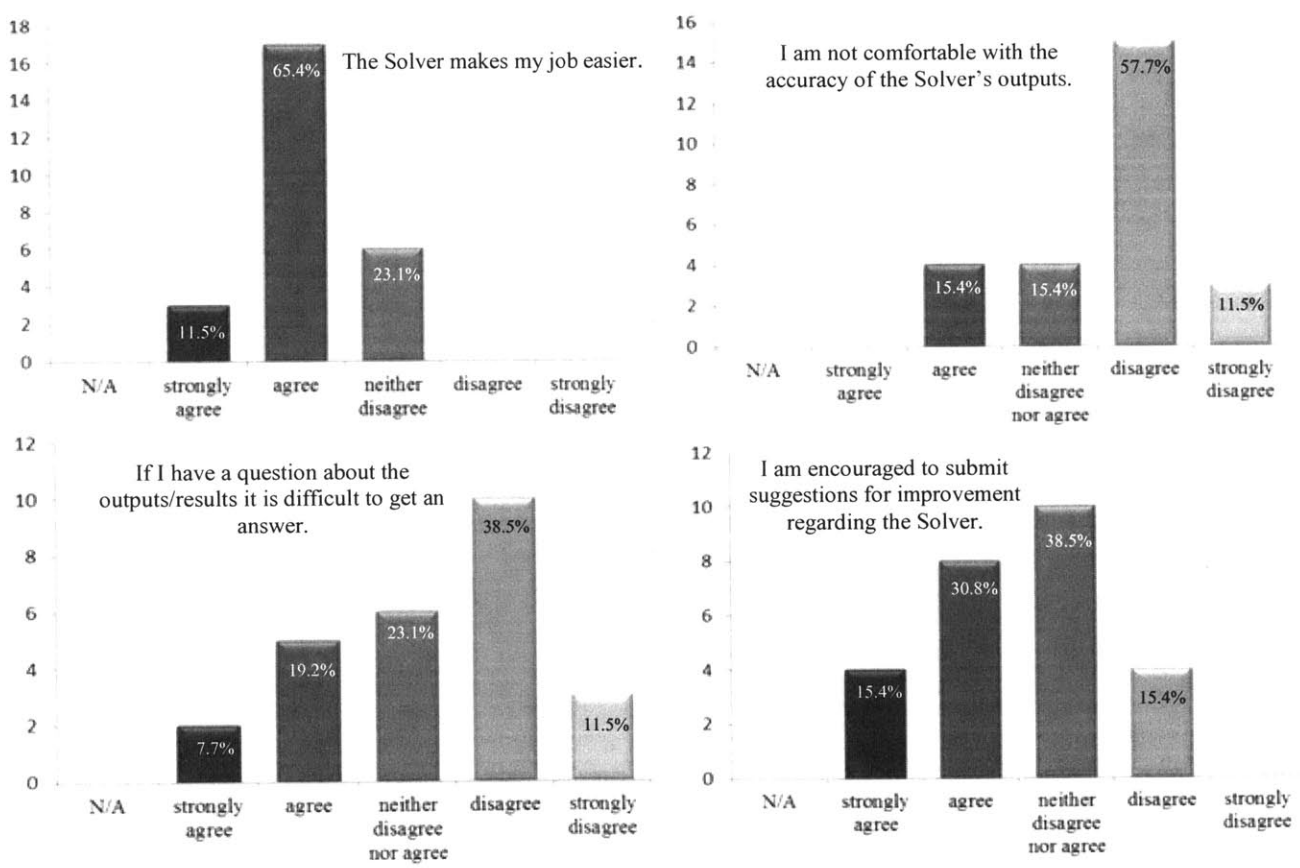

Figure 10 : Question 7 (Effectiveness)

4.1.4. Model Visualization

The final section of questions deals with Visualization of the optimization results. We used the first question to see whether the tool presents excessive information that is not relevant to the planner. Users are split fairly evenly, with 38.5% agreeing with the amount displayed, 30.8% neutral, and 30.7% indicating the tool displays too much information. The second question develops the first by asking if the displayed information is effective. We are trying to understand if users would better understand the outputs when presented in a different way. Again, users are evenly split. One problem with this question is that it doesn't provide an alternative visualization for the planners to make a relative decision.

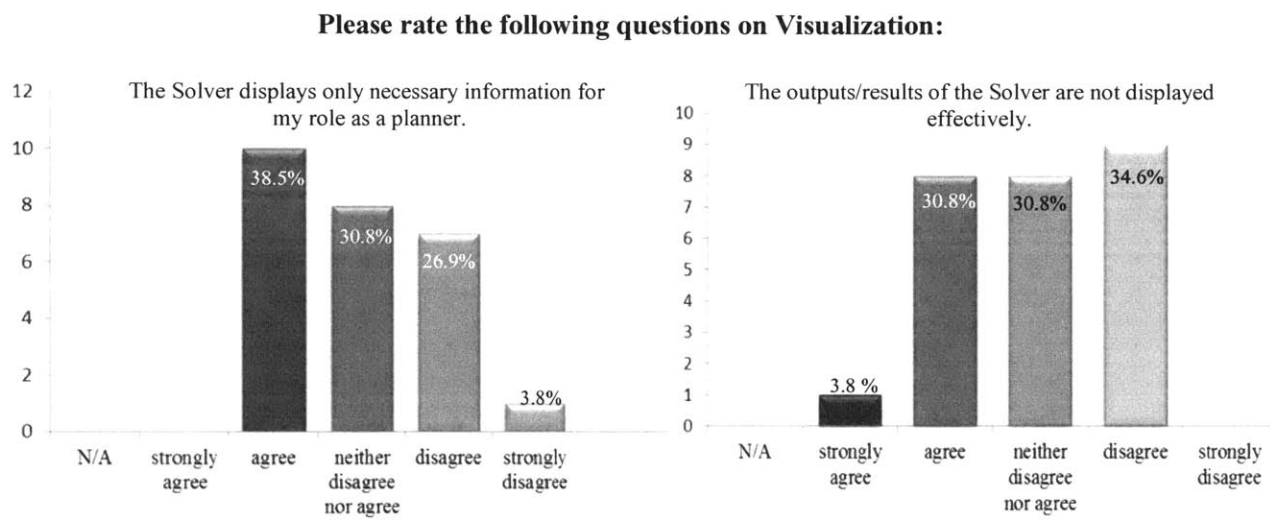

Figure 11 : Question 8 Results (Visualization)

4.1.5. Remedy Methods

Next, we looked at the various tools that planners use to communicate with others when getting help with the Solver. Respondents were able to check all that apply. Figure 12 reveals that POOL tickets, email, instant messenger, and in-person are the dominant communication mediums. Telephone is relevant, but not at the level of the others. Video conferencing is rarely used. The interesting finding is that many people do in fact speak in-person about the issues. Speaking in-person is a major contributor to communication effectiveness. Our hypothesis was that most of the communication is conducted electronically, which is proven wrong with these results. Over 65% of users speak in-person about their issues with the tool.

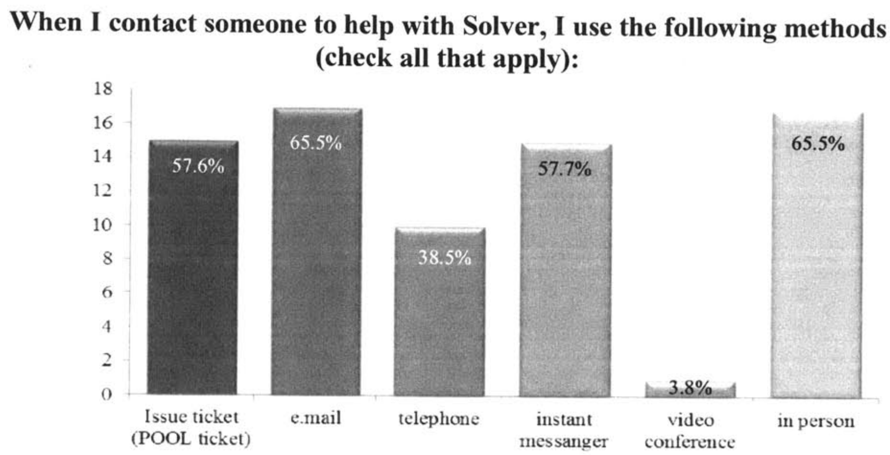

Figure 12 : Question 9 Results (Remedy Methods)

4.1.6. Crosstab Analysis

After analyzing the general responses, we looked at the crosstab responses to see how certain answers correlated with others. After searching through all combinations of answers, we selected five crosstab responses as the most important. As uncovered in the general responses, two themes were also found important in the crosstab analysis; training and visualization are catalysts for increasing communication and understanding.

4.1.6.1. Training

Figure 13 below presents the crosstab responses for user time and training adequacy. The responses tell us that new users do not feel that the Solver training was adequate while experienced users feel the opposite. We believe that this could be interpreted in two ways. The obvious first response is that the training is not adequate for new users of the tool. But, the company also has its most experienced users contradicting their answers. So, the training could become more valuable as it is mixed with experience. Thus, we will infer that the training has to be robust initially, but mixing it appropriately with experience is the key ingredient to success.

		How long have you been a user of the Solver?			
		less than 6 months	between 6 months and one year	between one year and 18 months	over 18 months
The training I have had on the Solver was adequate.	strongly disagree	16.7% (1)	0.0% (0)	0.0% (0)	0.0% (0)
	disagree	50.0% (3)	33.3% (1)	0.0% (0)	0.0% (0)
	neither disagree nor agree	0.0% (0)	0.0% (0)	0.0% (0)	23.1% (3)
	agree	33.3% (2)	66.7% (2)	80.0% (4)	69.2% (9)
	strongly agree	0.0% (0)	0.0% (0)	0.0% (0)	7.7% (1)

Figure 13 : Crosstab 1 (User time and training adequacy)

Alongside the responses in Figure 13, users responded similarly when asked about the last time they received training. Figure 14 depicts the crosstab of last received training and perceived training adequacy. Here, the users who received training within the last month were also the ones who were most likely to view the training they had received as inadequate.

		When did you last receive training on the Solver?			
		within the last month	between one and six months ago	between six months and one year ago	more than one year ago
The training I have had on the Solver was adequate.	strongly disagree	20.0% (1)	0.0% (0)	0.0% (0)	0.0% (0)
	disagree	60.0% (3)	0.0% (0)	12.5% (1)	0.0% (0)
	neither disagree nor agree	0.0% (0)	16.7% (1)	12.5% (1)	14.3% (1)
	agree	20.0% (1)	83.3% (5)	62.5% (5)	85.7% (6)
	strongly agree	0.0% (0)	0.0% (0)	12.5% (1)	0.0% (0)

Figure 14 : Crosstab 2 (Last trained and training adequacy)

4.1.6.2. Data Visualization

The crosstab analysis also revealed further details about the value of potentially incorporating data visualization techniques to facilitate greater understanding of the complex optimization tool. Figure 15 depicts the crosstab of simple to use and output results displayed effectively. The answers depict the notion that displaying results effectively affects the perception of how simple the tool is to use. The users who agree that the solver's results are not displayed effectively were more likely to respond that the tool was not simple to use. Conversely, the users who believe the tool is simple to use are more likely to disagree that the outputs are not displayed effectively.

		The Solver is simple to use.				
		strongly disagree	disagree	neither disagree nor agree	agree	strongly agree
The outputs/results of the solver are not displayed effectively.	strongly disagree	0.0% (0)	0.0% (0)	0.0% (0)	0.0% (0)	0.0% (0)
	disagree	0.0% (0)	27.3% (3)	16.7% (1)	**57.1% (4)**	**100.0% (1)**
	neither disagree nor agree	0.0% (0)	**36.4% (4)**	**50.0% (3)**	14.3% (1)	0.0% (0)
	agree	**50.0% (1)**	**36.4% (4)**	33.3% (2)	28.6% (2)	0.0% (0)
	strongly agree	**50.0% (1)**	0.0% (0)	0.0% (0)	0.0% (0)	0.0% (0)

Figure 15 : Crosstab 3 (Simple to use and results displayed effectively)

Next, we examined how the users' perception of understanding priority inputs was affected by their answers to visualization questions. Figure 16 displays the crosstab of adjusting priorities and displaying necessary information. This crosstab reveals that users who think extra information is displayed were more likely to answer that they didn't understand how inputs or priorities affect outputs. Alternatively, users who felt that only necessary information was displayed were likely to answer that they understood how inputs affected outputs.

		When I adjust inputs/priorities, I understand how they will affect the output.				
		strongly disagree	disagree	neither disagree nor agree	agree	strongly agree
The solver displays only necessary information for my role as a planner.	strongly disagree	**50.0% (1)**	0.0% (0)	0.0% (0)	0.0% (0)	0.0% (0)
	disagree	**50.0% (1)**	**40.0% (2)**	16.7% (1)	21.4% (3)	0.0% (0)
	neither disagree nor agree	0.0% (0)	**40.0% (2)**	**50.0% (3)**	21.4% (3)	0.0% (0)
	agree	0.0% (0)	20.0% (1)	33.3% (2)	**57.1% (8)**	0.0% (0)
	strongly agree	0.0% (0)	0.0% (0)	0.0% (0)	0.0% (0)	0.0% (0)

Figure 16 : Crosstab 4 (Adjusting priorities and displaying necessary information)

Finally, we looked at the crosstab of displaying outputs effectively and understanding inputs and priorities. Figure 17 reveals that users who perceive the outputs as not displayed effectively also believe that inputs and priorities are difficult to understand. Conversely, users that believe that outputs are displayed effectively also perceive the inputs as easy to understand.

		The outputs/results of the solver are not displayed effectively.				
		strongly disagree	disagree	neither disagree nor agree	agree	strongly agree
The solver's inputs/priorities are difficult to understand.	strongly disagree	0.0% (0)	0.0% (0)	0.0% (0)	0.0% (0)	0.0% (0)
	disagree	0.0% (0)	44.4% (4)	0.0% (0)	22.2% (2)	0.0% (0)
	neither disagree nor agree	0.0% (0)	33.3% (3)	50.0% (4)	11.1% (1)	0.0% (0)
	agree	0.0% (0)	22.2% (2)	50.0% (4)	44.4% (4)	0.0% (0)
	strongly agree	0.0% (0)	0.0% (0)	0.0% (0)	22.2% (2)	100.0% (1)

Figure 17 : Crosstab 5 (Displaying outputs and inputs difficult to understand)

4.1.7. Open Comments

Finally, we included two optional questions at the end of the survey to allow for open comments. The first question asked about the challenges, if any, faced by users. The second question asked for any additional comments.

Below, we separated the comments into the categories that were used earlier in the survey. Also, we added a category, other, to catch everything that didn't fall into Training and Expereince, Complexity, Effectiveness, or Visualization. Comments have been parsed for different ideas that were presented in one comment.

Training and Experience

"Understanding all that it can do then being able to work within those parameters. When you are constantly learning more about the capabilities of a tool, it begs the question of how effectively are you using it if you didn't know this back then"

"Refresher training would be helpful"

"Updated training materials"

"I want to learn how to use the Solver to run different analysis. If will be great if we can learn from other how to use the Solver to run different analysis"

"Lack of training"

Complexity

"Understanding most of the logic"

"Penalties are not clear. Solvers priority are not clear cut....demand first? how priority 4 works...how lock test schedule is prioritized in the solver."

"Solver error can be improved to help users to better understand what caused it."

"Understanding priority settings and how it influences Solver output"

"Firm grasp of formula calculations for solve output (WOI, how input PHIs are applied such as offsetting an input PHI against a supply output)"

"Being able to explain why the Solver gave certain results vs. the expected results"

"Investigating the root cause of not getting the expected results."

"Trouble shooting. The datalog on solve results are not clear. If you have a failed solve, it's hard to understand or look for the issue. Another problem changing the build plan. If the results are not desirable, sometimes it's hard to understand which knob to turn."

Effectiveness

"I like the Solver and allow it to run the jobs as intended with minimal input from the planner, the results match targets. The less the planner messes with it, the better the results."

"Hard to pin-point reasons for failed solves"

Visualization

"Reports are slow. GUI is hard to read. "

I want the screen input, report names to be the SAME for each solver. Why are they different?"

"Some of the data entry into the Solver is very manual and some reports show massive amount of data that is not relevant"

Other

"Lack of Excel functionality for input reports (copy/paste)"

"As a manager, don't have access to management summary reports, I'm having to pulse my planners to export and send out"

"It seems we do a lot of rechecking data each reset to ensure it is correct. WHY? What changes from ATM copy? It should be the same unless I change it so it seems like we cannot trust the data in the first place"

"A great tool for tackling very complicated linear optimization model."

"Why do we have to validate inputs every cycle - redundant to check data each time, data loads should be accurate and not need validation each cycle?"

"Only issue is that sometimes, when there is a 'system' issue, the closed loop process breaks."

The open comment questions revealed some interesting findings. First, it confirmed our hypothesis that users believe improvements can be made through increased training and improved GUI visualization techniques. Although there was not a majority share based on statistics, this still represented a significant portion of the surveyed population. Second, some responses contradict the ideas presented earlier in the complexity section. The previous answers indicated that users were reasonably comfortable with the inputs, outputs, and the effects of the priorities. However, we received the most comments in this area. Users want to understand more about why the Solver found the solution that it did. This points to an opportunity to invest in visualization pilots that will engage users in understanding optimal solutions. Finally, there were a few new ideas introduced in the other section that reflect areas for improvement, mostly in the realm of business processes.

4.1.8. Key Insights

To summarize the survey responses and crosstab analysis, we developed the following key insights for our sponsoring company:

- The understanding of, support for, and communication around the Solver is very high; Current processes should stay in effect with only minor changes.
- Initial and version-update user training should be robust and application-oriented to keep increasingly complex optimization tools in line with user expertise.
- Innovative data visualization techniques can increase understanding and lead to better communication between everyone involved with the optimization tool. Even though the lack of these techniques does not currently appear to be a barrier for the effective

use of the tool, this is an area that may increase user engagement. However, we did not find any empirical evidence that this will yield better decisions for Company X.

4.2. Interview Analysis

Though they were not structured interviews, we had many conversations with the Solver community that were recorded and analyzed for pertinent information. We felt that only one comment was raised during our conversations that was relevant to include as items to be considered by the experts and creators of the Solver. The idea of a "rollback function" was described by one planner (Anonymous Company X, Solver user, 2013). The planner desired functionality where they were able to look through old priority changes to see how they compared to current ones. The term, "rollback functions" is used to cover this area. Adding a rollback function would allow the user to analyze and better interpret how priority changes will affect future outcomes. Also, the user will undoubtedly be educated about the tool during the process. This is an area where visualization may be required to navigate through complex historic decisions.

5. OBSERVATIONS

Combining the results of the survey and interviews with our literature review, we arrived at the following observations for Company X; however, the findings are applicable to any organization attempting to align increasingly complex optimization models with a global capacity planning community. Initial training for planners might involve a combination of user interface orientation, appropriate levels of optimization modeling education, and timely version update training. From the crosstab analysis, we conclude that users perceive they have received insufficient training, and that the primary way in which these users acquire knowledge about the tool is on-the-job over time. We believe that visualization techniques may help increase the knowledge uptake rate.

5.1. User Training

From our own experiences with building smaller, representative optimization models and in response to the comments during the survey, we believe that a robust training program is a catalyst for improving communication by increasing user understanding of the models. A user that better understands the complexity involved in the algorithmic decision will better identify with and be more connected to a model of this size. Little (1970) described what we are trying to achieve as "…techniques of model design and implementation that bring the model to the manager and make it more a part of him."

From our research, we believe initial training should include user interface introduction combined with some form of modeling education, if not similar to what we experienced. Users should also have access to updated training materials in case they want to further their understanding on an individual basis. Next, as new model versions are introduced, an appropriate training package should be deployed to ensure the planning community understands what has changed. With such a complex tool, the survey results indicate that it is easy for the model to outpace the capability of the user. Thus, it important to keep both elements, the user and the model, moving ahead at the same pace. There are various ways to accomplish this action; training can be decentralized to the individual, site, or regional areas, or it can be centralized with the experts as the training managers. Either way, it is important to keep the global team on the same level of understanding.

5.2. Incorporating Data Visualization with Optimization Modeling

In this section we outline current use of visualization techniques, and examine some contemporary approaches and tools. It should be noted that given the rapid pace of software technology evolution the tools that are described in this paper as new or contemporary could soon be considered outdated.

5.2.1. The case for Data Visualization

While computers can be excellent at discerning patterns from large and complicated data sets, human beings are typically not. As mentioned in the literature review, Conway (2012) illustrated that the way we humans perceive data differs greatly from the way that machines do. By using huge streams of data, and leveraging visualization techniques it is often possible for human observers to discern outliers and patterns in the data that would be virtually impossible to notice if one were to observe only the raw data.

The DIMES project (Shavit, Y., 2012) is a scientific research project which aims to study the structure & topology of the internet. Chris Harrison, a Carnegie Mellon University computer science Ph.D student took source data from the DIMES project and created a series of visualizations based on router to router connections. In total, there were almost 90,000 connections. Harrison is quick to point out that the mappings represent only the density of connections, and not the number of users (this is important, because for people in the developing world, many users may share a single connection – as in the case of an internet café). (Harrison, C., 2007).

Harrison created three graphs that display how the internet is connected. The intensity of contrast in these graphs reflects the number of connections between the two points being connected.

In the first of his three graphs (figure 18), although Harrison does not explicitly show country borders or geographic features it is very clear that we are looking at a world map. It is also clear where the highest density of router to router connections sits – between the United States and Europe. The data that Harrison used to produce this graph is from 2007, therefore one should assume that the picture today will look rather different.

Figure 18 : Data visualization of worldwide router connections in 2007 (Harrison, C., 2007)

Figure 19 below shows the second of Harrison's graphs, where the outline of the European Union can be easily recognized. Additionally, even with no map present, the major cities can be readily determined based on the relative concentration of router connections.

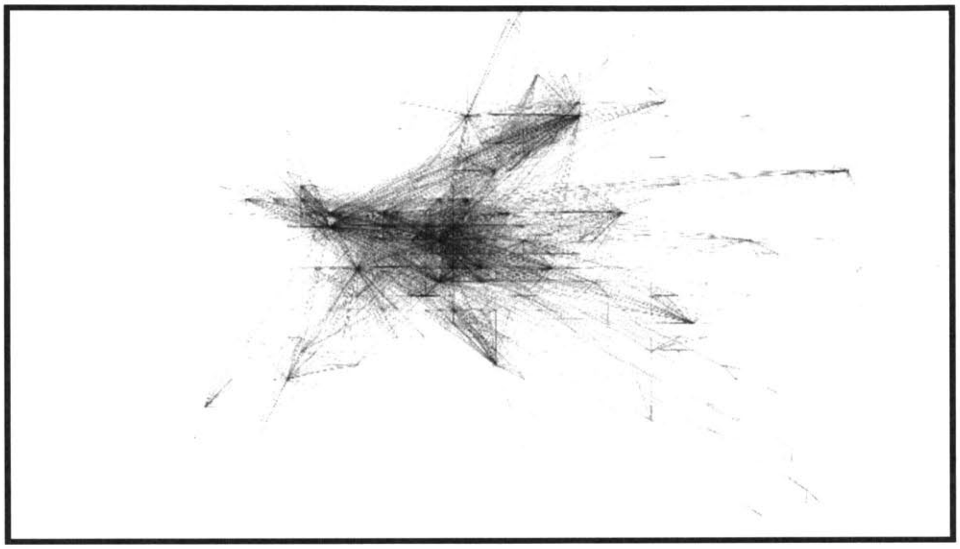

Figure 19 : Data visualization of European Union router connections in 2007 (Harrison, C., 2007)

Finally, in Figure 20 we can clearly see the outline of the United States. The major cities can be readily determined, and we can also see that a large concentration of router connections link the Northeastern US with California.

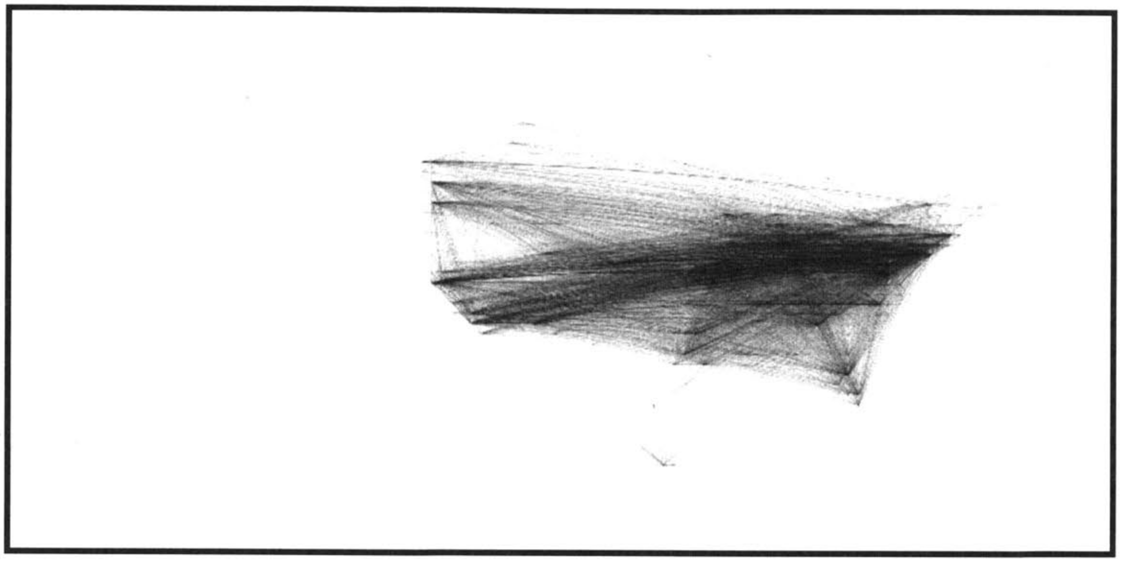

Figure 20 : Data visualization of United States router connections in 2007 (Harrison, C., 2007)

While Harrison's graphs are visually appealing in an artistic sense, there is also a clear potential for practical utility here as well, especially in supply chain management where global complex networks are pervasive. In Harrison's project, 90,000 router-to-router connections were used. Even with the use of sophisticated analytics tools, it would still take significant time and a non-trivial amount of effort to draw the kind of inferences that you can make in seconds by using a visualization tool like Harrison's graphs. Additionally, the viewer doesn't need to be a data scientist with a Ph.D to intuitively understand what he or she is seeing. It is very clear to any observer of Figure 20 that they are looking at the United States. Equally clear is that the highest density of router to router connections lies between the Northeastern US and California.

The business usefulness of Harrison's graphs is still questionable. Figures 21 and 22 present a data visualization approach that enables a human to intuitively assess patterns in very complicated data sets. In many cases, the patterns that need to be assessed may require a degree of subjective inference and understanding of the problem context. These types of subjective inferences are often better handled by a human with a visualization tool than contemporary computers which tend to be better suited to objective, highly rational tasks. One such task where this approach has proven to be of particular value is evaluating planetary data collected by the Keplar telescope.

The Keplar telescope, which was launched in 2009, was designed to help discover earth-like planets which orbit far-away stars. While the process that is used to determine whether there are orbiting planets around a star is relatively simple to understand, the data that needs to be collected is substantial and the method required to analyze the data is rather subjective. In Figure 21, the X-axis represents time in days and the Y-axis represents the brightness level of the star.

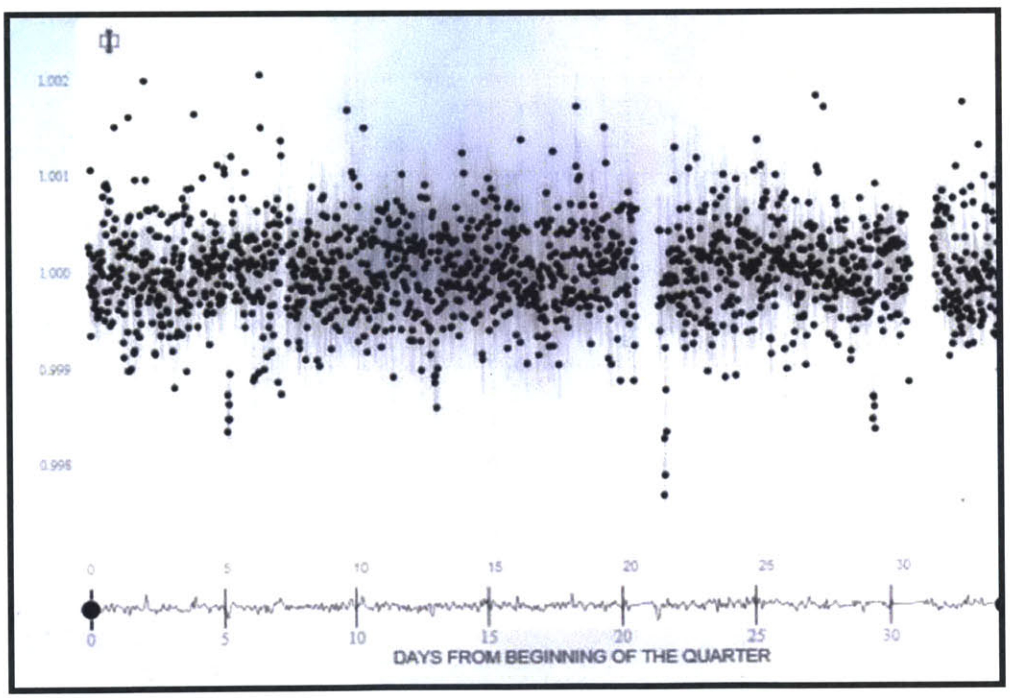

Figure 21 : A star's data gathered from the Keplar telescope (planethunters.org, 2012)

The purpose of the chart shown in Figure 21 is to map how the brightness of a star changes over time. As a planet passes in front of a star, a very slight decrease in the light intensity seen from the star can be detected. Depending on how far the orbiting planet is from its star, several dips may be traceable in the light-curve. Figure 22 highlights the transit dips that can be discerned from the non-highlighted Figure 21.

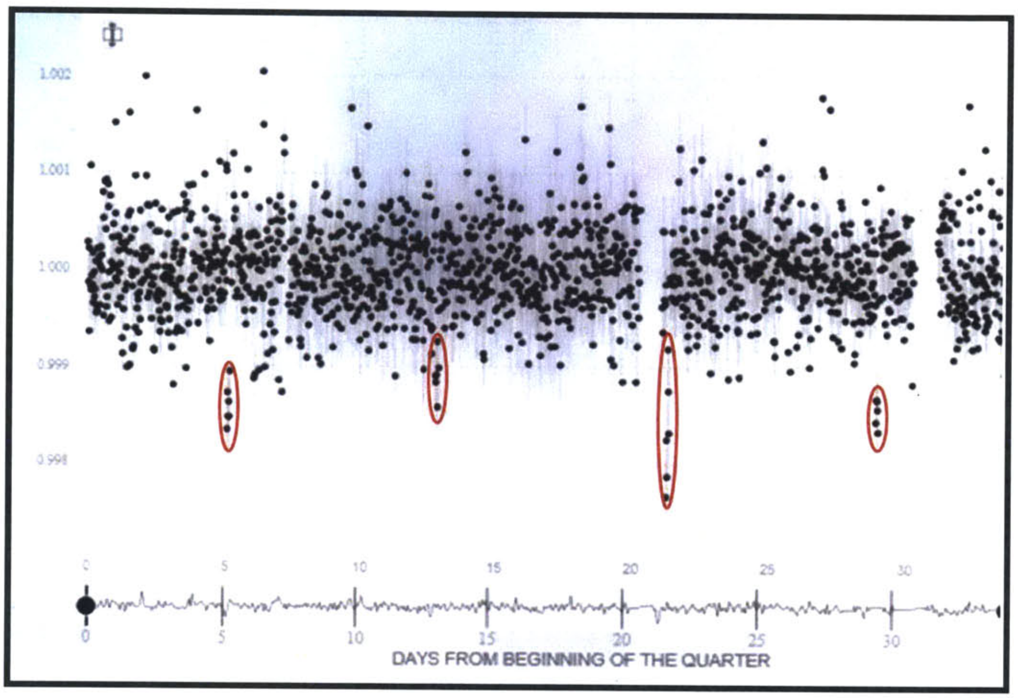

Figure 22 : Highlighted "transient dips" from Keplar telescope (planethunters.org, 2012)

In the example shown in Figures 21 and 22, there are some clearly discernable light intensity decreases. However, many other samples of Keplar data are less obvious and the analysis can be difficult and highly subjective.

While it may well be possible to train computers to at least eliminate stars where there are clearly no transit dips, a final positive confirmation will most likely require human eyes for the foreseeable future. At the time of writing, the Keplar telescope is set up to monitor the brightness of more than 145,000 stars in a fixed field of view. To date, it has found over 2000 candidates, and the list is growing. This is clearly a massive undertaking, and would be virtually impossible without data visualization and human validation. In the case of optimization models with thousands of parameters and constraints, creating this type of "outlier identification" chart will allow business users to focus attention on areas of high risk.

By use of a third example (Figure 23), we examine a piece of work by Jer Thorpe, a data artist from New York. Thorpe created a data visualization to capture Twitter "tweets" that contain the phase "just landed in." He then parsed the location that the user had just landed in, along with the user's listed home location from their Twitter profile, and used this to map the travel pattern of worldwide Twitter users (Thorpe, 2009).

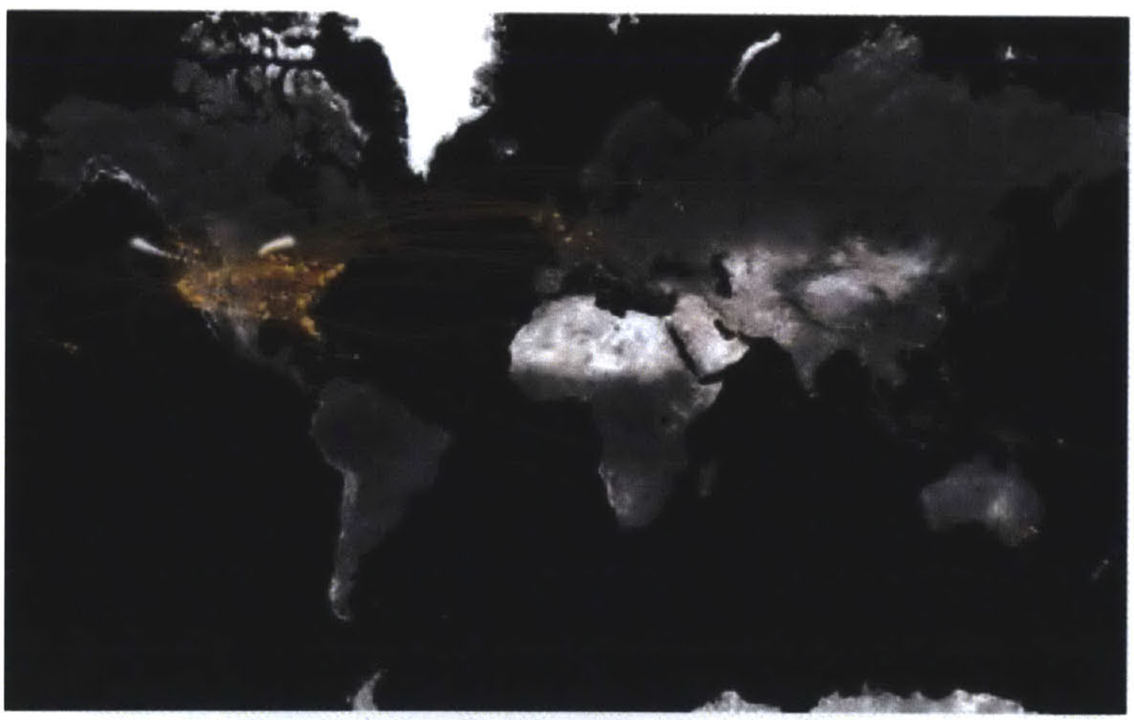

Figure 23 : Screenshot of Jer Thorpe's "Just landed" visualization (Thorpe, 2009)

While Thorpe's work is interesting intellectually, others have taken similar approaches with much larger data sets to address very difficult problems. For example, data scientists at Google noticed that certain search terms can be good indicators of flu activity. Detecting the spread of the flu virus early on can enable rapid response efforts, which in turn can lessen the impact of flu outbreaks. By aggregating search data, Google has been able to estimate the spread of flu activities almost in real-time (Ginsberg, J. et al, 2009). These types of visualizations illustrate how "external data" can be used to supplement decision-making and understanding. For example, by tracing "expedite-orders" in an active production schedule, future scheduling decisions may be improved.

In this section, we have examined a variety of interesting uses of data visualization techniques. However, the user of an optimization tool may wonder how this type of approach might help them with their task of interpreting the output results of the model that they use. While this is not a simple question to answer, in the next section we propose a framework to enable the users and designers of optimization tools to select an appropriate visualization approach that will best fit their specific situation. Caution is urged here, because technology alone will not address the communication challenge. Good, general design practice as espoused by Edward Tufte (1983) and Stephen Few (2006) and described in the literature review section are at least of equal importance when selecting a visualization approach to data communication.

5.2.2. Proposed visualization tool evaluation framework

There is currently a wide array of tools, frameworks and approaches that can help facilitate the task of information visualization. As companies evaluate the approaches and options that make the most sense to them, we believe it is helpful to take a high level view of the tools that are available, and understand to what types of uses those tools are best suited.

In his book, "Computer Simulation in Management Science," Michael Pidd (2004) presents an approach to classifying simulation tools. Here, we propose leveraging Pidd's framework to help classify data visualization tools and approaches. The tools mentioned are intended to be a representative sample, and not a comprehensive list of all available choices. Additionally, for this study, we have only considered the data visualization capabilities of those tools that we evaluated. While many of these tools have very rich and robust feature sets that expand far beyond visualization, we have not considered additional features in this analysis.

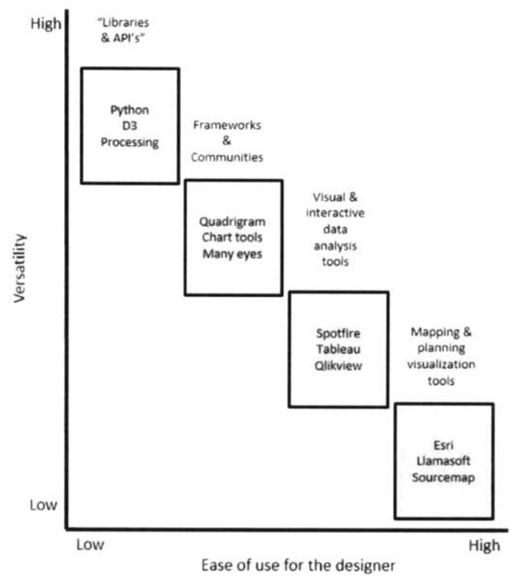

Figure 24 : Data visualization tool classification (derived from Pidd's approach)

Explanation of the four primary categories:

The matrix shown in Figure 24 uses Pidd's framework for classifying simulation tools and proposes a preliminary overview of the categorization of current data visualization tools and approaches. For example, by reviewing the matrix in Figure 24 we can immediately see that while the category of "mapping & planning visualization tools" in the lower right-hand corner provides the greatest ease of use, the data visualization versatility of the tools in this category is severely limited and therefore typically suited to very specific uses. At the opposite end of the spectrum, in the upper left-hand corner of the matrix, we can see that the category of "Libraries and APIs" provides tremendous versatility, but requires the purposeful dedication of time and expertise in order to derive meaningful use. Also, as tools and technologies mature there is a tendency to "pre-package" visualizations for ease-of-use and by doing so adding more flexibility. Nevertheless, the overall framework remains valid.

"Libraries & API's":

The category of *"Libraries & API's"* refers to a set of tools that would be used by developers for creating bespoke applications or for customizing pre-built ones. We now provide a brief description of the sample of tools we included in the matrix shown in Figure 24. All of the tools in this category enable the custom development of the visualization. The presentation format of the data is only limited by the creative and technical skills of the designer.

Python is a general purpose high-level programing language that has gained popularity because of its relative ease of use, portability across computing environments, widespread deployment and comprehensive standard library.

D3, which stands for Data-Driven Documents, is a JavaScript library for manipulating documents based on data. Since it is JavaScript based, its output can be seamlessly presented through standard web browsers. See Figures 33 through 38 for examples of visualizations created using the D3 framework.

Processing is an open source programming language and environment used to create images, animations, and interactions.

"Frameworks & communities":

The category of *"Frameworks & communities"* refers to a category of tools that, similar to Libraries & API's, are intended for use by developers. However, this category takes the development process a step further, and provides ready-made charts and tools that can be used as the starting point for the development effort, to save developers from re-inventing from scratch each time they begin a new endeavor.

Quadrigram is a tool for building interactive and highly personalized data visualizations. Several illustrative examples of the types of visualizations that can be produced using Quadrigram are shown in Figures 29, 30, 31 and 32.

Google Chart Tools provide a way for developers to visualize data on their websites. Google provides a broad array of chart types that can easily be populated with data by using client and server-side tools that Google provides with the charts. A screenshot of some typical chart tools that Google offers is shown in Figure 28.

Many eyes is an IBM Research project and website whose stated goal is to enable data analysis by making it easy for laypeople to create, edit, share and discuss information visualizations.

"Visual & interactive data analysis tools":

The category of *"Visual & interactive data analysis tools"* refers to a class of tools that focus on making the exploration of large volumes of data accessible to sophisticated end users.

Spotfire, Tableau, and Qlikview are all Business Intelligence tools that allow users to explore and represent large data sets. We present two simple demonstrative screenshots of Tableau visualizations in Figures 26 and 27.

"Mapping & planning visualization tools":

The category of *"Mapping & planning visualization tools"* refers to a class of tools that enable the geographical plotting of components, to facilitate the effective planning and management of supply chains. Unlike the libraries and frameworks mentioned earlier, these applications are packages, and intended end users from a variety of backgrounds and with varying skill levels. Showing data in a geographic map format can often highlight patterns in the data that might otherwise be difficult to see.

Esri is a sophisticated mapping Software that enables the visualization of data in a geographic format.

Llamasoft is a Software vendor that produces Supply Chain Planning tools. Part of the functionality that is offered includes visual mapping of supply chains in a geographic format.

Sourcemap is an easy to use web-based tool for helping visualize global supply chains through the use of a geographic map layout. An example of a simple Sourcemap visualization is shown in Figure 25.

5.2.3. Visualization examples

In this section we have compiled examples of visualizations from selected tools studied.

<u>Mapping & planning visualization tools</u>

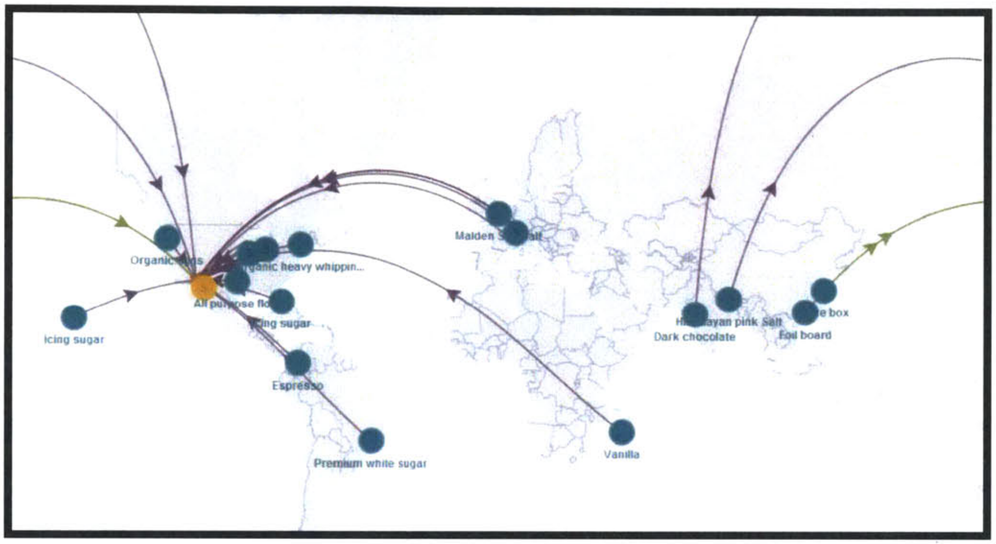

Figure 25 : Example of Mapping & Planning visualization tool (Sourcemap, 2013)

Figure 25 above is a screenshot from the supply chain visualization tool Sourcemap. The tool fits into the "Mapping & planning visualization tools" category of the Data visualization tool classification approach proposed in Figure 24. We have included this visualization because it provides a good example of a tool that while easy to use, has an output that is highly interactive and logically straightforward.

On the next page, Figures 26 and 27 are screenshots from a tool produce by Tableau, which falls under the "Visual & interactive data analysis tools" category shown in Figure 24. These visualizations demonstrate how supply chain and logistics related data can be quickly compared and interacted with when presented in a visual format.

Visual & interactive data analysis tools

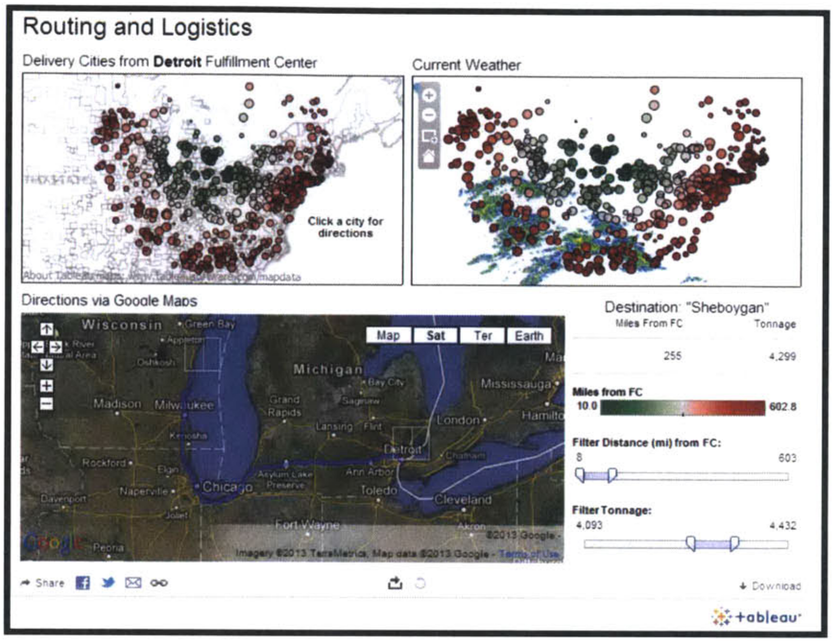

Figure 26 : Examples of a visual & interactive data analysis tool (Tableau, 2013)

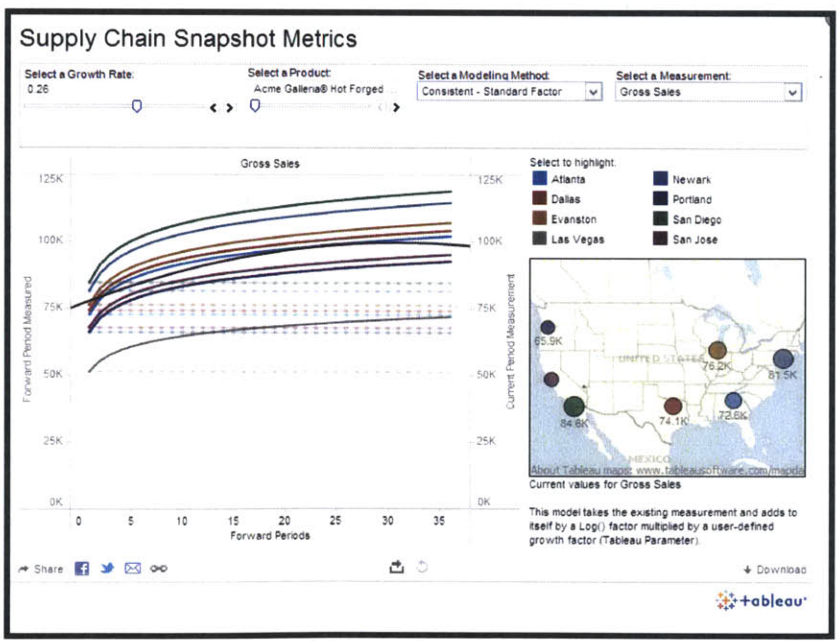

Figure 27 : Second example of a visual & data analysis tool (Tableau, 2013)

Frameworks & communities

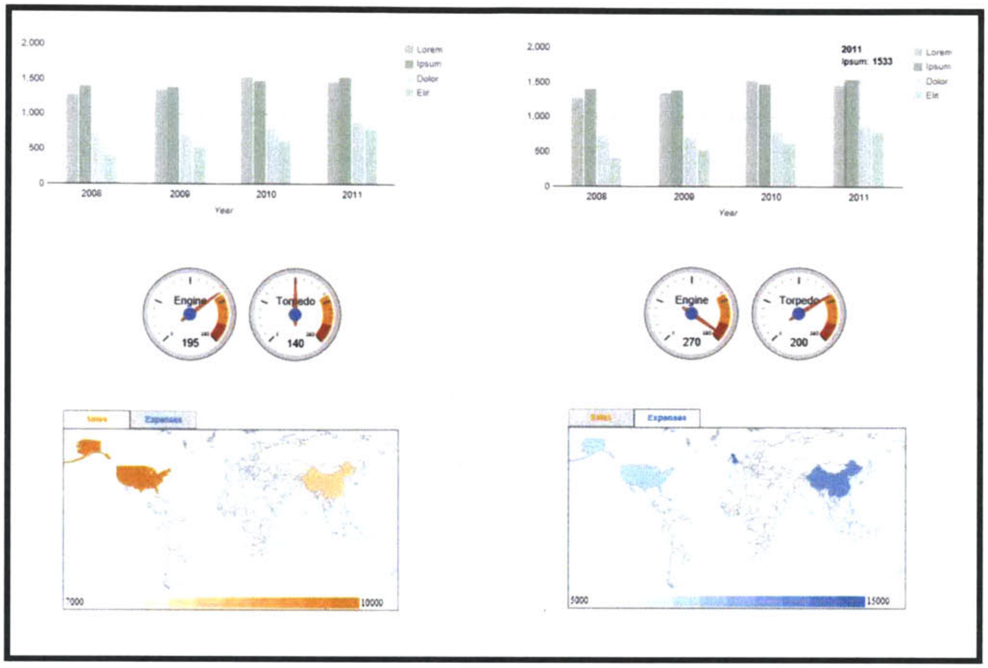

Figure 28 : Example of a visualization framework using Google Chart Tools (Google, 2012)

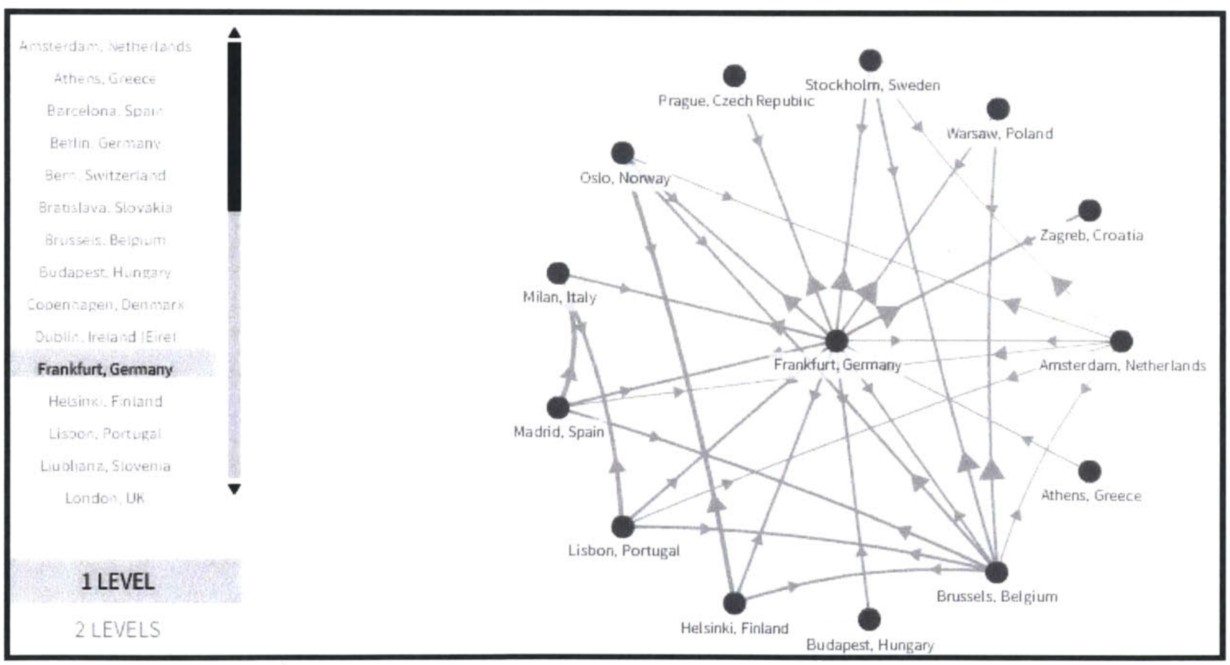

Figure 29 : Visualization framework - air traffic routes (Quadrigram.com, 2013)

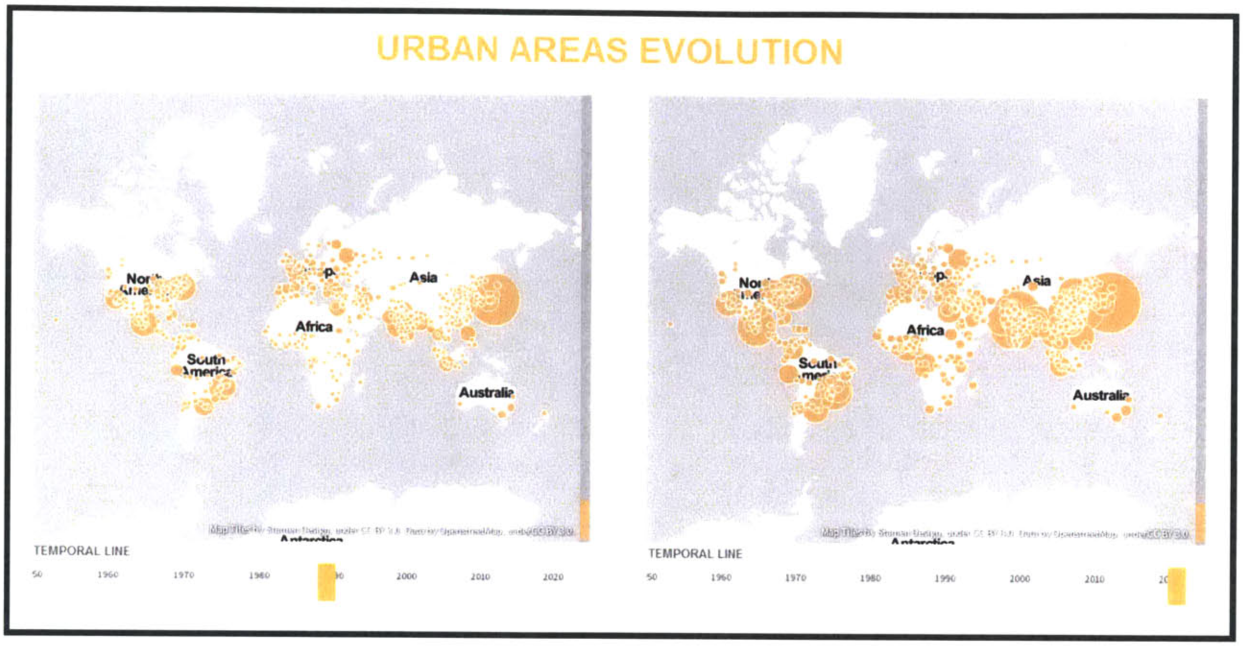

Figure 30 : Visualization framework - world population growth (Quadrigram.com, 2013)

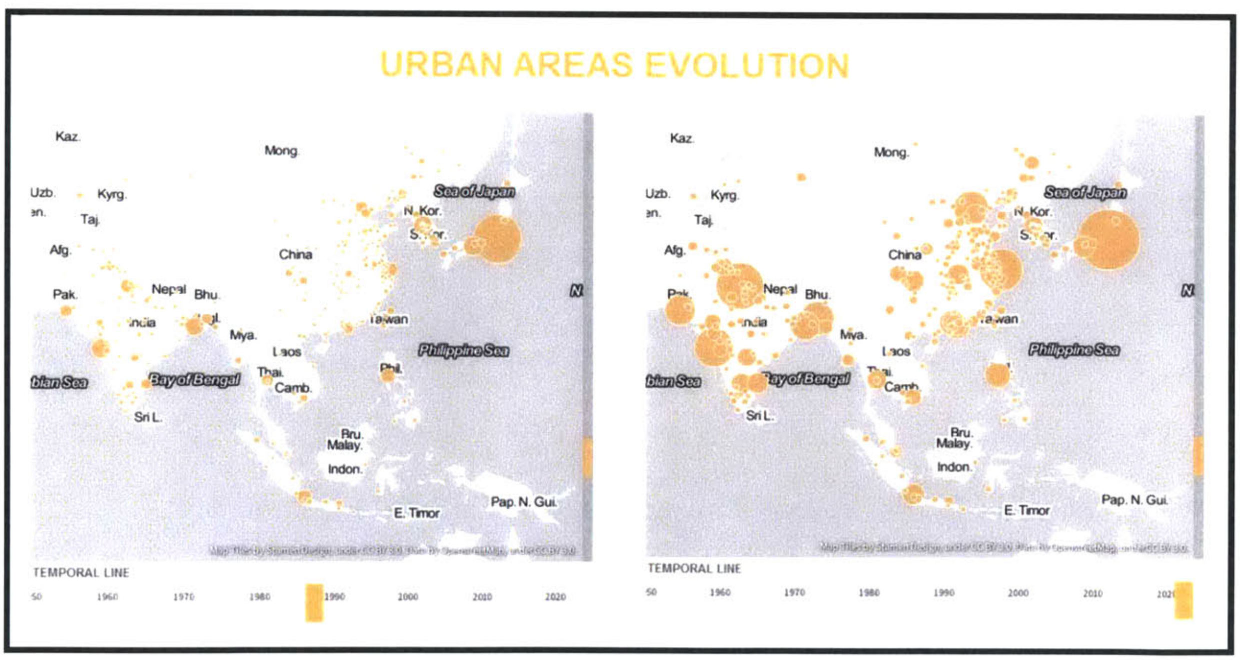

Figure 31 : Visualization framework - Asia population growth (Quadrigram, 2013)

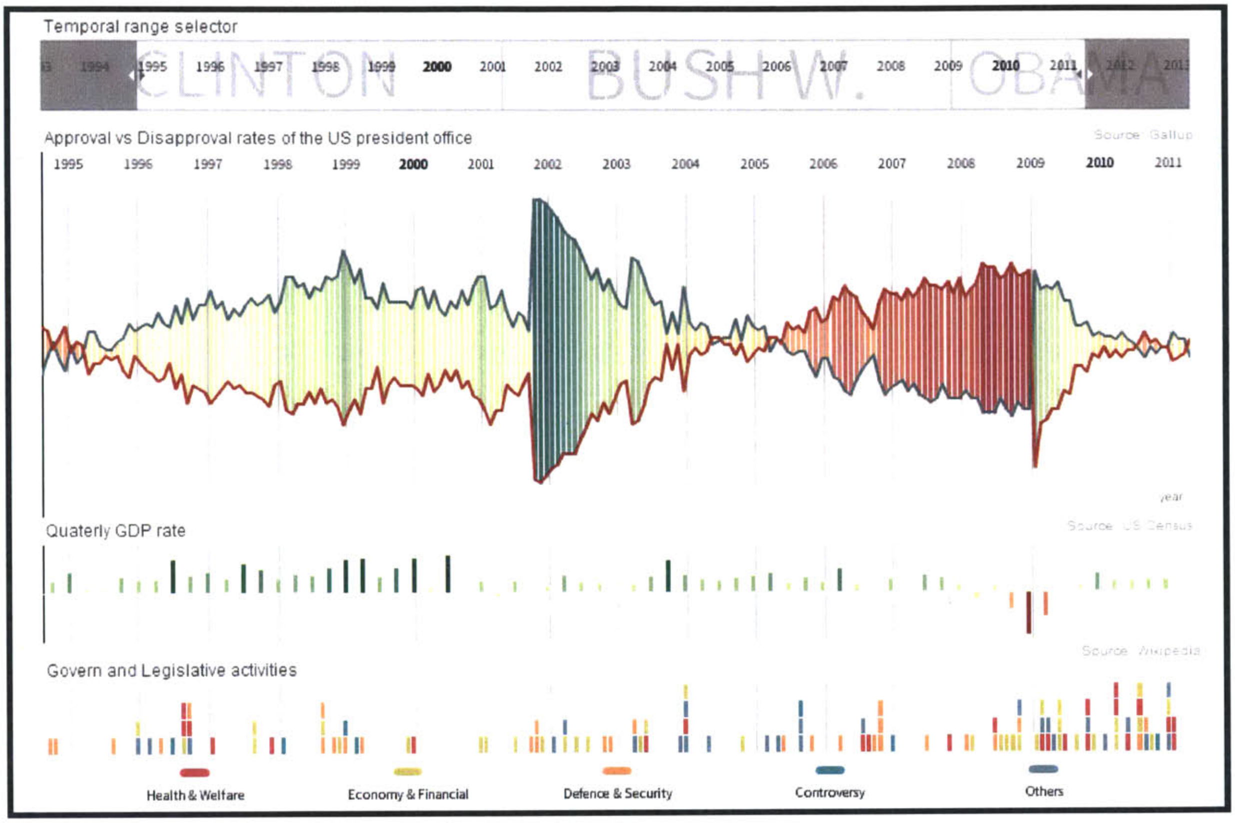

Figure 32 : Visualization framework - popularity of US presidents (Quadrigram.com, 2013)

Figure 28 shows some of the chart objects that are available from Google chart tools. These tools allow for a feature rich, easy to understand and interactive end-user experience without the need for substantial custom code development and maintenance.

The Quadrigram visualizations shown in Figures 29 through 32 illustrate the wide variety of presentation styles that can be used without having to adopt a fully customized approach. For example, Figure 29 enables the user to evaluate network routes at the click of a button, and filter the selections by use of a slider. The chart is dynamic, and if the user clicks on any node in the chart the node will automatically shift itself to the middle and the entire chart will dynamically reorganize. This approach has significant potential for the analysis of transportation routes and various types of network.

Figures 30 and 31 illustrate a simple form of animated sensitivity analysis. In each case, a geographic region is shown (Figure 30 shows the entire world, while Figure 31 shows Asia), and by use of a slider the user can quickly compare population density between different time periods. We have included these charts because we believe that this type of sensitivity analysis could prove very useful when comparing different sets of optimization model results.

Figure 32 shows the relative popularity of the last three US Presidents. With less than a minute of review, the end-user can clearly determine that the Monica Lewinsky affair actually did very little to affect Clinton's popularity rating and that the 9/11 attack provided a major boost to Bush's rating. We have included this chart because presenting data in this format, and in an interactive manner, has significant potential to enabling the quick identification of trends in large, aggregated data sets.

On the following pages, Figures 33 through 38 visually show data related to the mass shooting events that have impacted the US over the past 30 years. Nanda Yadev (2013) has created a simple to use, yet compelling visualization tool based on source data from the Mother Jones news website (Follman, M. et al, 2013). We have included this visualization because within a very short period of time, the viewer can gauge the scale, frequency and fatality level of each incident. Through the use of a menu at the top of the screen, Yadev enables the end-user to instantly view the data from any one of eight dimensions. Five of the eight dimensions are shown in Figures 33 through 38, and they are location (33), whether the shooter had any prior signs of mental illness (34), whether or not the weapons were legally acquired (35 & 36), gender of the shooter (37) and year of the event (38). Figures 35 and 36 illustrate that if the end-user wishes to find out more about a particular incident, then he or she need only click on the item and they are presented initially with summary level detail, and by clicking again they receive detailed information about the selected incident. Having data presented in this form, will enable the user to quickly understand the detail behind the results they receive.

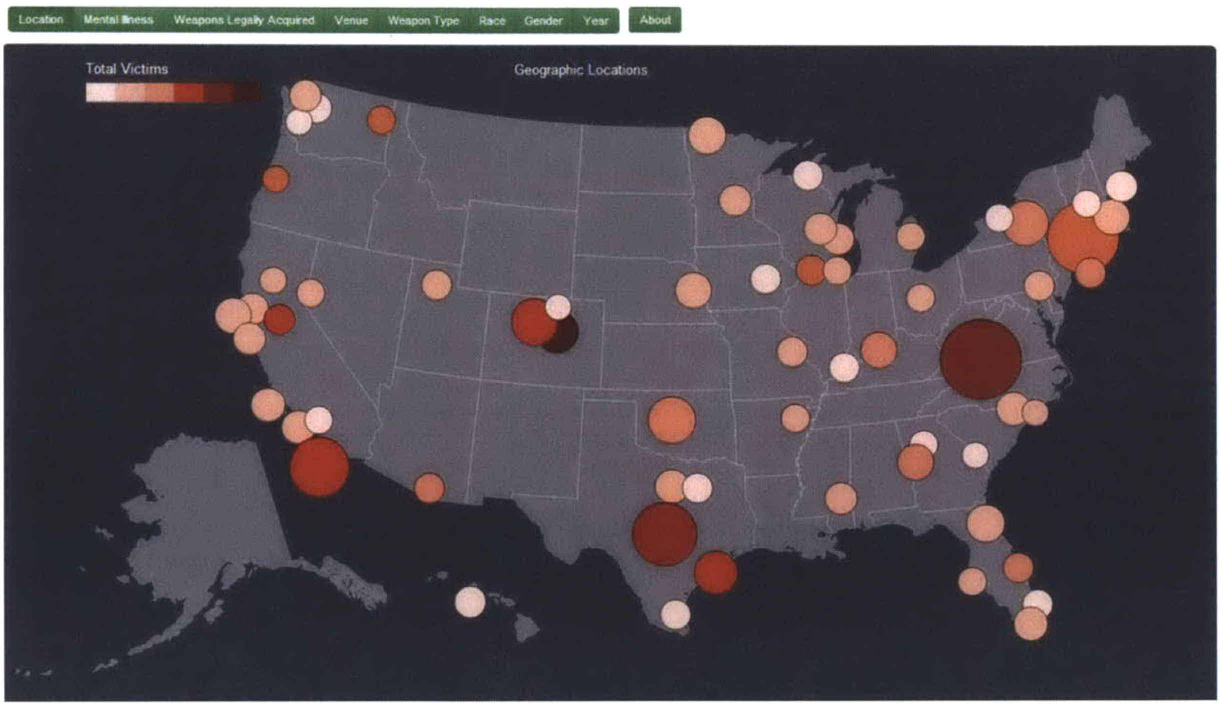

Figure 33 : Example of Library built visualization view (Yadev, 2013)

Figure 34 : Example of a Library built visualization - mental illness view (Yadev, 2013)

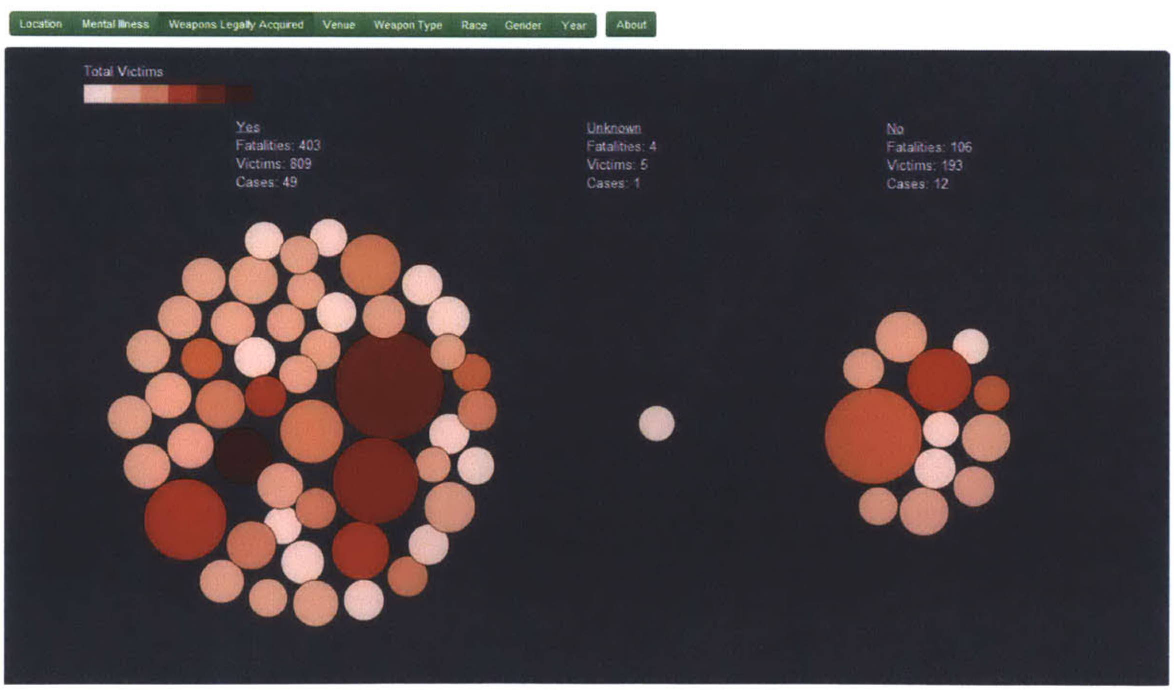

Figure 35 : Example of a Library built visualization – legally acquired view (Yadev, 2013)

Figure 36 : Example of a Library built visualization - summary level detail (Yadev, 2013)

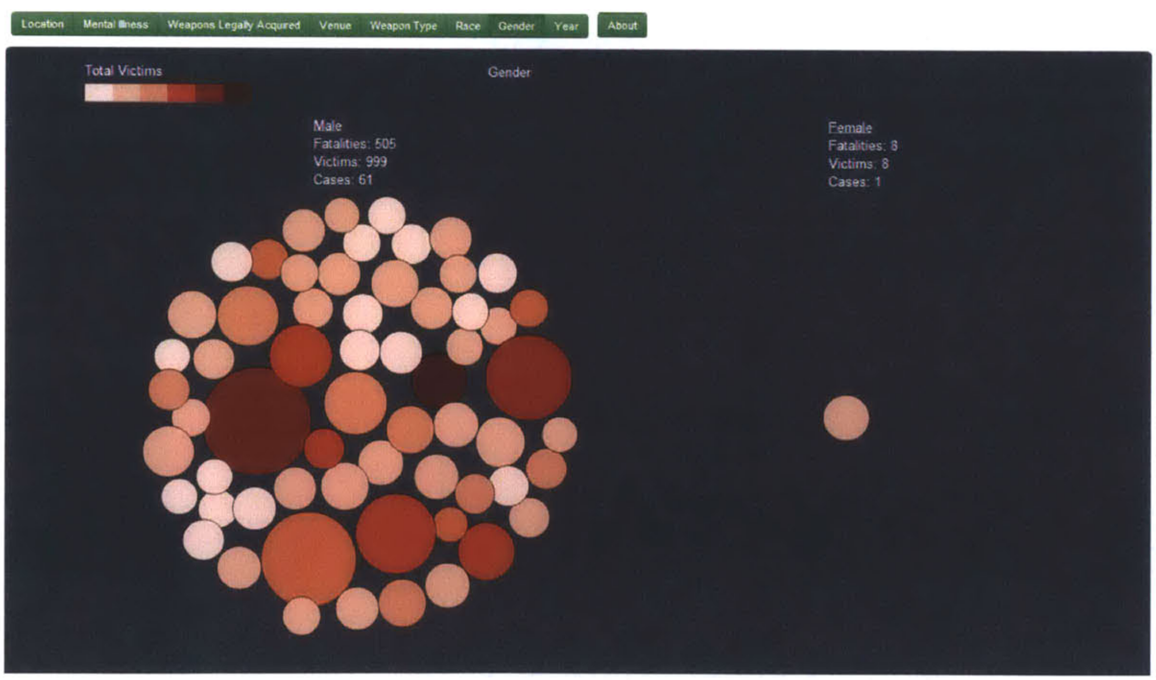

Figure 37 : Example of a Library built visualization - gender of the shooter (Yadev, 2013)

Figure 38 : Examples of a library built visualization - year of incident (Yadev, 2013)

Figures 39 and 40 show a 3D globe animation that enables the end-user to very quickly evaluate a geographic region that is of interest.

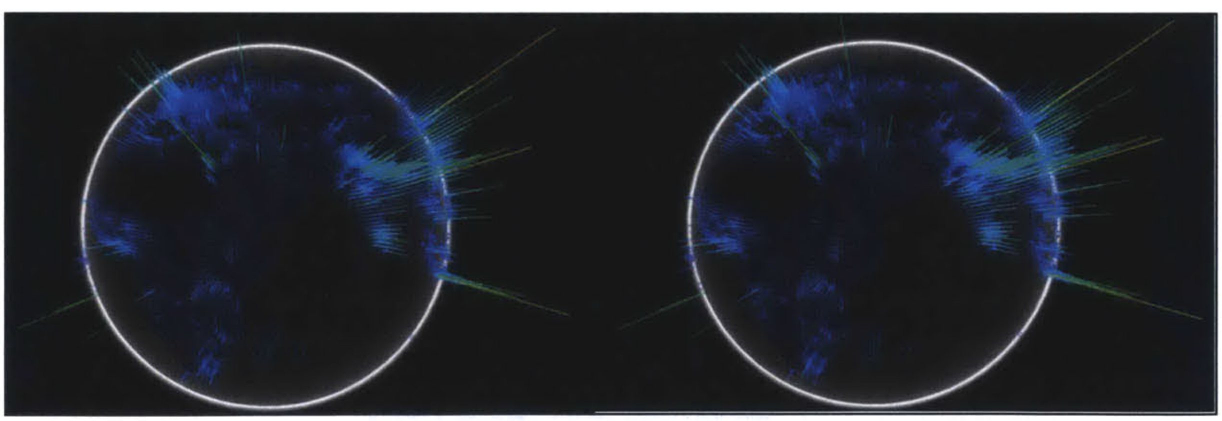

Figure 39 : Examples of a 3D animated visualization mapping population growth (Mangini, 2011)

In Figure 39, Renato Mangini incorporates a slider function along with a 3D globe animation to quickly enable the end user to compare population growth over a given time period.

We have included this visualization because we believe that this type of highly interactive animated sensitivity analysis will become increasingly prevalent within analysis tools for enterprise customers.

In Figure 40, Nicolas Belmonte has used the same animated globe display as Mangini, and this time presents flight transportation routes. This approach would allow for a significant expansion upon the very simplistic 2D view provided by Sourcemap in Figure 25.

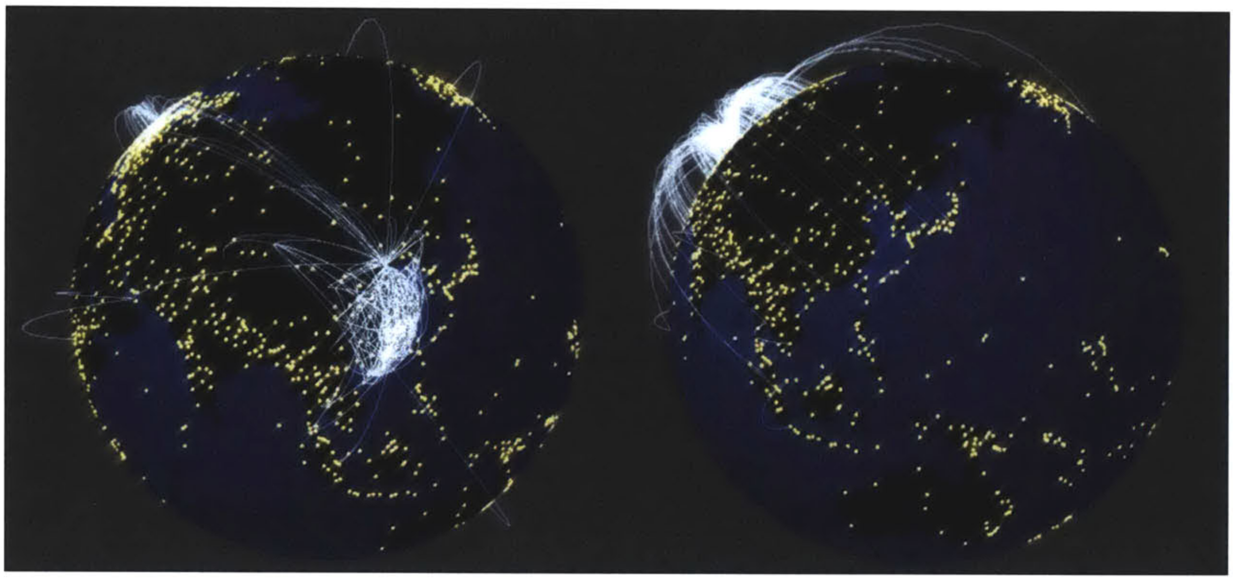

Figure 40 : Examples of a 3D animated visualization mapping air routes (Belmonte, 2011)

While 3D globe animations are not currently featured in enterprise software tools, we believe it is likely only a matter of time before they will be. At the time of writing, 3D animation and the types of advanced sensitivity analysis we have reviewed in this section are featuring more in the tools that end-users engage with on their home PC's (for example, Google Maps and analysis tools for personal finance). It is highly likely that these same end users will come to expect equivalent functionality inside of the tools they user while performing their roles at work.

5.2.4. Considerations for Company X

By reviewing the matrix in Figure 24, and comparing it with what we know about Company X's Solver, we are able to make the following high level observations:

1) Given the current utility and success of the Solver, a low versatility tool may not provide much new value to the activities currently covered by the tool.
2) Company X's OR team is well positioned to potentially leverage some of the advanced capabilities in the "Low ease of use" and "High versatility" quadrant.
3) Feedback from the planner surveys indicates that there could be a place for a well-planned and carefully structured information dashboard that could sit on top of the existing tool.

While care must be taken to ensure that Tufte's (1983) and Few's (2006) design principles are reviewed and understood before a specific technical tool or framework is chosen, it is clear that there is real potential for improving the planner experience through the use of visually oriented information dashboards. Actual tool choice must be considerate of the needs of the users as well as the expertise level that exists within the operations research team.

For an organization like Company X, with a mature and capable optimization team that includes several talented developers, we believe that the greatest potential for improvement lies in the upper two tiers ("Libraries & API's" and "Frameworks & Communities") of the Data visualization tool classification approach proposed in Figure 24. While there may be some potential use for tools from the lower two tiers ("Visual & interactive data analysis tools" & "Mapping & planning visualization tools") within Company X as a whole, we do not see a compelling need to attempt to incorporate these tools into the Solver.

In terms of a reasonable adoption curve for these types of technologies, it is recommended that Company X's optimization team evaluate some of the tools that fit into the "Libraries & API's" and "Frameworks & Communities" section. We then recommend that the team develop a series of representative visualization rapid prototypes by working closely with some representative end-users of the Solver tool. It is likely that the best forum for this type of activity would be in the form of a series of 1-2 day workshops. This approach would not only enable the developers from the optimization team to gauge where to apply visualization to maximize its impact, but it will also help generate some excitement within the end-user community regarding the upcoming new release. It is recommended that the optimization team implement new visualizations incrementally, and only with clear acceptance from the end-users. By taking an incremental approach, and engaging with the end-users throughout the process, the likelihood of the approach being useful will be dramatically increased.

6. CONCLUSION

This paper started with an introduction to the communication barriers that exist when deploying complicated optimization tools to manage global supply chains at corporations like our sponsor, Company X. Then, we presented an extensive literature review of optimization modeling, communication techniques, and data visualization. Incorporating what we learned from the review, we developed and completed a survey of optimization tool users. Using general and crosstab analysis of the responses, we concluded that users were very supportive of the tool and its capabilities; however, they want to understand the tool's outputs better. With a tool this complex, understanding and communicating these results can be an arduous task.

To any organization facing this challenge, we recommend using a robust training program that includes appropriate amounts of application and experience with the tool. We believe that this approach will help prevent future communication barriers through increased understanding of the tool. We also presented current data visualization tools that are relevant to supply chain management and others that are used in various industries. Many of the visualizations are cutting-edge and nascent in their connection with optimization modeling. Pushing the envelope and developing visualizations applicable to optimization modeling could have a dramatic impact on user's understanding and how well they can communicate with developers of the tool. We hope to see future research and progress in this area so that users and experts are able to communicate fluently and effectively use complex optimization models for managing global supply chains.

7. APPENDIX

Exhibit 1: Survey

1. How long have you been a user of the Solver?

- less than 6 months
- between 6 months and one year
- between one year and 18 months
- over 18 months
- I have never used the Solver

2. How many hours per week (on average) do you spend using the Solver?

- less than two hours
- between two and five hours
- between five and ten hours
- between ten and twenty hours
- more than twenty hours

3. Please rate the following questions on your understanding of Company X's Supply Chain.

	strongly disagree	disagree	neither disagree nor agree	agree	strongly agree	N/A
I have a good understanding of Company X's global supply chain.						
I have a good understanding of my location's role in Company X's supply chain.						

4. When did you last receive training on the Solver?

- I have never received training
- within the last month
- between one and six months ago
- between six months and one year ago
- more than one year ago

5. Please rate the following questions on Training and Experience.

	strongly disagree	disagree	neither disagree nor agree	agree	strongly agree	N/A
The training I have had on the Solver was adequate.						
Additional training about the solver would be helpful.						
Additional experience with the solver would be helpful.						

Exhibit 1 cont'd: Survey

6. Please rate the following questions on Complexity.

	strongly disagree	disagree	neither disagree nor agree	agree	strongly agree	N/A
The Solver is simple to use.						
The solver's inputs/priorities are difficult to understand.						
When I adjust inputs/priorities, I understand how they will affect the output.						
The solver's outputs/results are difficult to understand.						

7. Please rate the following questions on Effectiveness.

	strongly disagree	disagree	neither disagree nor agree	agree	strongly agree	N/A
The Solver make my job easier.						
I am not comfortable with the accuracy of the solver's outputs.						
If I have a question about the outputs/results, it is difficult to get an answer.						
I am encouraged to submit suggestions for improvement regarding the Solver.						

8. Please rate the following questions on Visualization.

	strongly disagree	disagree	neither disagree nor agree	agree	strongly agree	N/A
The solver displays only necessary information for my role as a planner.						
The outputs/results of the solver are not displayed effectively.						

Exhibit 1 cont'd: Survey

9. When I contact someone for help with the Solver, I use the following methods (check all that apply):

- [ ] issue ticket
- [ ] email
- [ ] telephone
- [ ] instant messenger
- [ ] video conference
- [ ] in person

Other (please specify)

10. (Optional) What, if any, are your challenges with the Solver?

11. (Optional) If you have any comments regarding the Solver, please add them below.

12. (Optional) We would like to contact Solver users for a brief follow-up phone interview. If you can assist with this request, please fill out the fields below.

Name:

Job Title:

Email address:

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