Business Information Visualization: Guidance for Research and Practice

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Dr. Ping Zhang
School of Information Studies
Syracuse University
Syracuse, NY 13244
Pzhang@syr.edu
(315) 443-5617
(315) 443-5806 (fax)

Business Information Visualization is a relatively new field and has just started to gain researchers' and practitioners' attention. Similar to Scientific Visualization and Information Visualization, it is intended to consider human cognition and perception characteristics and provide insight into data by computer generated visual representations. However, owing to the nature of business data, Business Information Visualization faces special challenges such as dealing with non-geometric data and incorporating human problem-solving processes. In research and practice, there is a need to understand the specific challenges of visualizing business data and the procedures of how to do it. This paper gives a brief overview of the history and development of Business Information Visualization. It then presents a methodology for developing business information visualization systems to enhance human problem solving and decision-making. This methodology includes one proposition, three technical challenges, and four stages in a visualization model. The author then presented a visualization system where this methodology is applied. Finally, the author discusses several issues that researchers and practitioners need to face.

1 INTRODUCTION

In most management domains, problem solving and decision-making are overwhelming because of the high volume of complicated data, the multiple complex relationships among data, the negotiability of the constraints, the changing environment, and time pressure. Most existing computer systems, such as expert systems, decision support systems, and simulation systems, have built-in functionality and cannot reflect a changing environment that requires possibilities for negotiation. Although they can generate reports, they are very limited in providing superior solutions for complex problems.

The power of visual association in our daily life is amazingly large. "Our daily vocabulary is full of words that do not literally transmit their significance but convey their meanings by visual associations. For example, we admit that we have understood others by saying 'I see." We give an 'overview' of our statements, 'preview' what we re going to study, and 'review' what we have learned already. A person with limited 'vision' is 'shortsighted.'" (Zhang 1995, p1)

There are basically two distinct purposes of visual associations or inventions: communicating and discovery. Communicating requires ideas to be carried by appropriate visual means. Discovery, on the other hand, requires exploration, comprehension, model development, and idea generation or creation. It is about a person searching for the "truth" or patterns in the sea of data. Communication of the data occurs after one finishes discovery.

Using different graphical or visual representations of scientific or business data (such as line charts, pie charts, bar charts, etc.) for comprehension and communication has been well practiced since early in this century or even earlier (Croxton & Stein 1932). These types of charts, however, are challenged by the characteristics of data that are more frequently encountered in today's scientific computing, computer simulation, managerial decision-making and problem solving. The volume of these data is exponentially large and the complexity of the relationships among data are beyond any traditional charts can represent.

Scientific visualization evolved to meet the ever-increasing need to deal with highly active, very dense data sources, which, for example, included satellite data, geophysical data, and data from supercomputer computations. It means using computer-generated graphics to help people understand and clarify visually the relationships inherent in data (Rosenblum & Brown1992). Scientific visualization emerged in the late eighties as a key field in computer science and in numerous other application domains such as geoscience, meteorology, medicine, etc. Scientific visualization provides processes for steering the data set and seeing the unseen, thereby enriching existing scientific methods (Kaufman 1990, 93). McCormick et al. (1987) state that it transforms the symbolic into the geometric, enabling researchers to observe their simulations and computations. Most scientific visualization systems are natural representations of real world objects that have known geometric structures. Thus the limitation is that one may not be able to transfer the procedures of scientific visualization directly for all possible applications, especially in managerial areas.

Information visualization is "a process of transforming data and information that are not inherently spatial, into a visual form allowing the user to observe and understand the information. This is in contrast with scientific visualization, which frequently focuses on spatial data generated by scientific processes." (Gershon and Eick 1995) Development of information visualization systems in the recent half decade has been fruitful. To represent abstract information and data visually, Information Visualization employs techniques of interactive and non-interactive computer graphics, imaging, perception, and design. Some of the key challenges involve inventing the visual metaphors, geography, and interactive techniques to extract knowledge and discover structure in rich and widespread datasets. Unfortunately, many existing information visualization systems do not emphasize on how a human solves problems and how information visualization can enhance human problem solving processes. Its concerns have been primarily visual representations including animation and interactive manipulations of the visual images.

Business Information Visualization "is a process of creating appropriate computer-generated visual representations of large amount of non-geometric managerial data for human problem-solving and decision-making support" (Zhang 1995). Business Information Visualization is a relatively new field and has just started to gain researchers' and practitioners' attention. On the one hand it is similar to Scientific Visualization and Information Visualization and is intended to consider human cognition and perception characteristics and provide insight into data by computer generated visual representations. On the other hand, Business Information Visualization has unique characteristics in the data to be visualized and how the visualizations could be connected to human problem solving or decision-making processes. Large quantities of abstract, non-geometrical data and complicated relationships overwhelm the decision-makers, especially when they are under time pressure. This situation exists almost everywhere, but especially in the managerial domains. For problem-solving and decision-making tasks, human beings are the ones who explore the sea of data during problem-solving processes. Thus, Business Information Visualization faces special challenges in dealing with non-geometric data and incorporating human problem-solving processes.

In research and practice, there is a need to understand the specific challenges of visualizing business data and the procedures of actualizing it. This paper presents a methodology of developing business information visualization systems to enhance human problem solving and decision-making. This methodology includes one proposition, three technical challenges, and four stages in a visualization model. A visualization system for manufacturing production planning is introduced to illustrate the application of the methodology. The author then discusses several issues that researchers and practitioners need to face.

2 A HUMAN-CENTERED PERSPECTIVE AND SOME CHALLENGES

Hamming (1962) has pointed out: "The purpose of computing is insight, not numbers." The same holds true for business information visualization. The purpose is not the final pictures or visual representations. It is the insight the pictures or visual representations can deliver to business users. The ultimate goal of visualizing managerial data is to enhance the interaction between decision-makers and the domain data, thus supporting decision-making activities and better human performance during the entire managerial problem-solving process.

Any decision-making support system or problem-solving support systems should be developed from a human-centered perspective. A BIV system should provide a human decision-maker with a coherent environment. In a collaborative way, BIV systems function as a cognitive aid to humans so that they can incorporate BIV into his or her own intelligent system to achieve higher intellectual goals than could be achieved before. A human-centered visualization system thus should help users to achieve cognitive effectiveness and efficiency by shortening cognitive distance from visual representations and removing mediation for thinking (Zhang 1999). The following is our underlying philosophy or proposition for visualizing business data.

Proposition: *A Business Information Visualization system should enhance the interaction between humans and information from a "data representation - task fit" perspective; as such it will have positive impact on human decision-making and problem solving performance.*

There are three technical challenges when designing information visualizations:

1. How to link data representations to tasks so that human information interaction can be enhanced.

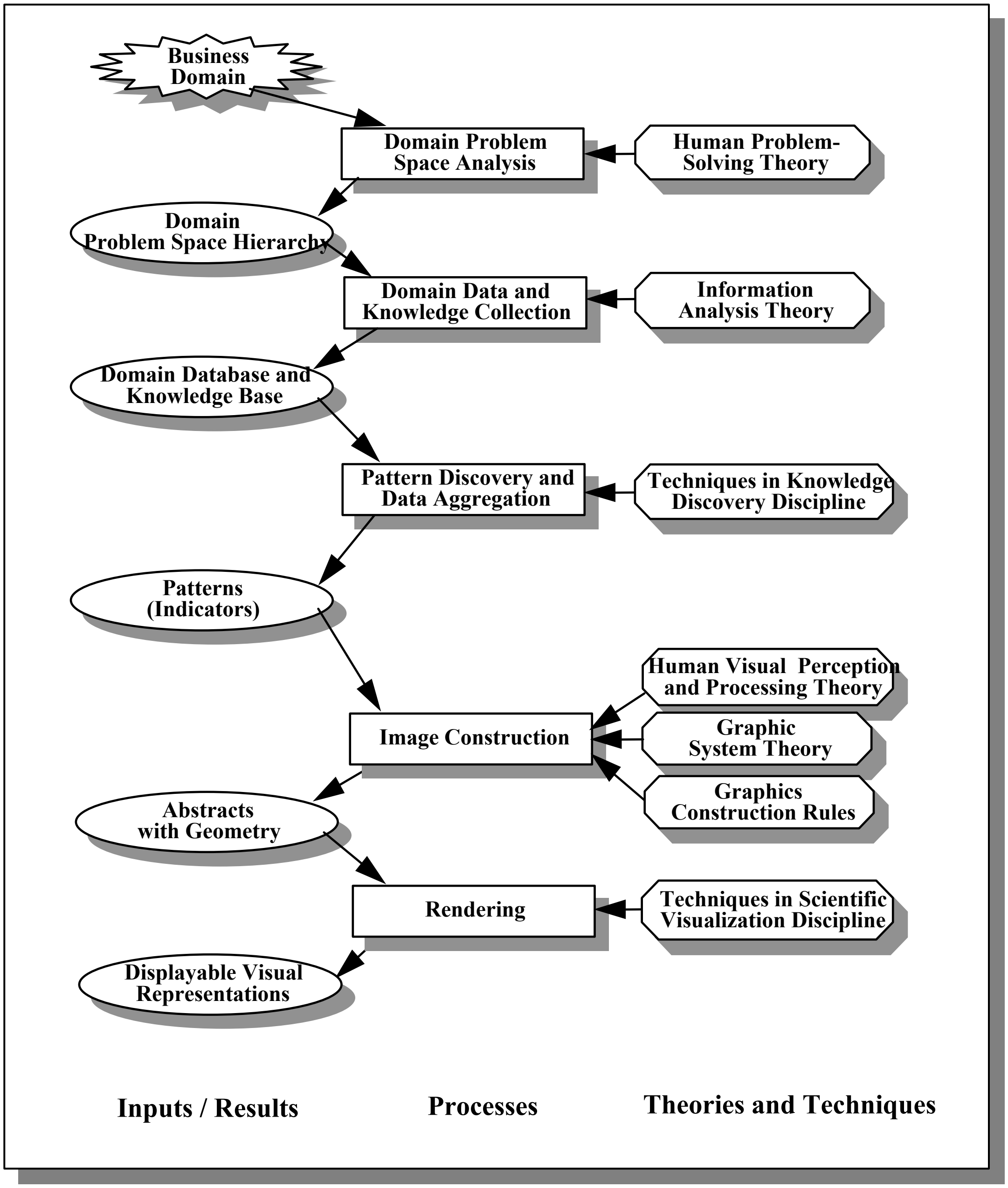
2. How to handle massive data in respect to both size and dimensionality.
3. How to configure the geometric structures for the data and the relationships among the data.

3 A VISUALIZATION MODEL

Business Information Visualization is domain specific and dependent on user takes and the characteristics of the data to be visualized. The final visualization representations thus may not and should not be all the same. BIV research and practice, however, need guidelines from both theoretical and practical perspectives so that the research and practice can be conducted in a principled, consistent, and disciplined way, rather than in a piecemeal, ad hoc fashion.

The general visualization model we are presenting here is based on our preceding work (Zhang 1995, Zhang & Whinston 1995, Zhang 1996, 1998). It shows the procedure for developing a business information visualization system for problem-solving support for any specific business domain. The stages indicate necessary actions and are means of managing the visualization project. There are iterations among different stages and the procedure does not represent a linear series of actions. Figure 1 depicts the general visualization model. It contains processes (rectangles), input or output of each process, and theories or techniques that each process may benefit from.

Figure 1. A General Visualization Model



3.1 Domain problem space analysis

This process is about the users and tasks of the business domain. One needs to analyze what types of problem human beings have to solve in a specific business domain, how they solve the problems, and how they evaluate the solutions before starting to design visual representations. Some problem-solving models, such as Simon's (1976), can be used as guidelines for studying domain problems and tasks, and how users solve problems. The user interface of a visualization system should support the human problem-solving activities during the entire problem-solving process and improve the problem-solving performance. Domain problems should be decomposed into tasks human decision-makers deal with. The outcome of this step is the domain problem space with criteria for evaluating alternatives.

3.2 Domain data and knowledge collection

Next is to detail what data the decision makers need in order to solve their problems, what relationships exist among the data, and what types of rules apply to the problem-solving activities. This step is a detailed, further analysis of domain tasks and can be guided by information analysis theory (Bertin 67) and the general rules for knowledge base construction developed in the Artificial Intelligence discipline. It starts from the problem space; analyzes each node in the problem space, as well as the entire problem space; identifies each data object and information component (variable), the characteristics of the information components, and the relationships among information components. The final collection of data is stored in a database. The relationships among variables and rules that apply to problem-solving activities are described as a set of knowledge and form a conceptual knowledge base. By "conceptual" we mean that the knowledge does not have to be represented within a knowledge representation formalism in forms of production rules, semantic networks, first order logic, etc. The final representations for the knowledge are realized by the visual representations.

3.3 Pattern discovery and data aggregation

This is a special step for dealing with the massiveness of the data in both volume and dimensionality. Due to the nature of a display space and the characteristics of a graphic system (Bertin 1967), only a limited number of information components (variables) with limited length (limited elements in the variables) can be displayed. However, in the business world, it is typical that decision-making involves multiple information components, and some information components have almost unlimited elements. Two major concerns are: First, among the multiple relationships in the data, how do we find the subsets of the relationships (which involve a subset of information components) that are most interesting or most important to the decision-makers and that should be displayed? Second, how can we compress an information component with unlimited elements into effective indicators that are displayable in size? The final data aggregation and compression are domain and task specific.

Knowledge Discovery in Databases (KDD) is a research frontier for both database technology and machine learning techniques, and has sustained research over recent years (Wu 1994). The essence of KDD is the nontrivial extraction of implicit, previously unknown, and potentially useful information from (large and noisy) data (Frawley et al. 1992). KDD encompasses a number of different technical approaches such as clustering, data summarizing, learning classification rules, finding dependency networks, analyzing changes, and detecting anomalies (Piatetsky-Shapiro 1994, Matheus et al. 1993).

It can be beneficial to use the techniques in KDD to find those relationships among information components that are most interesting to the decision-makers. The important relationships discovered (called patterns) could also be used to guide the data aggregation for the information components. The interplay between data mining and KDD and visualization indicates an iteration of the data exploration and discovery process. It could also be the case that visualization is used for data mining.

3.4 Visual representation construction

This stage handles issues of how to lay out non-geometric data and relationships (patterns) properly. It involves creation of images and is determined by human visual perception characteristics (Caeli 1981), the cognitive process of visual information processing (Kaufmann 1979, 80, Bertin 1967), and the characteristics of graphic systems (Bertin 1967) such as the perceptual properties of the visual variables. The goal is to create efficient images with legibility (Bertin 1967). The outcome of this stage is a set of abstract objects with "geometric" structures that may be in 2D, 3D, or MD space. Zhang (1998) designed specific image construction techniques for visualizing managerial data. These techniques have been tested by two Business Information Systems and can be generalizable to a number of business domains.

Once visual images are designed, the rendering step makes sure that multiple dimensions can be represented properly on a 2D surface. It includes projection from higher dimensions to 2D, rotation, scaling, clipping, and perspective mapping. Existing scientific visualization techniques (e.g. Nielson et al. 1990) can be applied.

4 AN EXAMPLE OF A VISUALIZATION SYSTEM

In this section, a visualization system is briefly presented in order to illustrate the visualization model in the previous section. Interested readers can refer to Zhang (1995) for more detailed descriptions of the system where more visual images are provided.

The visualization system is developed for manufacturing production planning of an Electronic Card Assembly and Test (ECAT) plant at Austin, Texas. In manufacturing production planning, a planner's goal is to maximize overall revenue from the production, subject to resource constraints such as tools and components availability. A typical manufacturer can have hundreds of different products and thousands of different components. Some of the components are used by several different products and thus are named "common components." Different production assembly lines (also called Production Pull Lines, or PPLs) share tool capacity and components during production. A production plan can span several weeks. The decision-making environment is dynamic. For instance, there often is a severe component shortage problem. Among all short components, however, only a very few components are “critical” or bottleneck components. During the planning period, planners can take many possible actions in order to solve some of the problems or sub-problems. For instance, they can change the quantity of products to be made in each week (this is called demand), can move demand to different assembly lines to change production loads, or can move demand to different time periods within the same assembly line. They can adjust an assembly line’s capacity by adding or removing tools. They can change the quantity of components to be received (that is, scheduled receipts), and change the distribution of components over products (named production mix). In such a dynamic environment, the planner’s understanding of the planning problem situation is crucial.

Owing to the complicated relationships among data and the dynamic decision-making environment, existing production planning systems, such as various MRP II systems (some of them available at ECAT) and some simulation systems, could not provide complete solutions for production plans that reflect the changing constraints and environment. Some of these systems had friendly user interfaces and provide simple one- or two-dimensional graphs (line charts, bar charts, pie charts, etc.) of certain data. However, most data these systems could provide were in tabular format: they were either limited to the size that a computer screen could handle, or printed as a report that might be several hundred pages long. Data displayed in these ways did not give planners a clear vision of what was going on. In other words, they showed "trees" but not the "forest" of the planning problems. Before trying any possible actions, the planners needed to use their cognitive powers to figure out the “stories” behind the data, such as identifying the critical components from all shortfall components.

The problem space for production planning is depicted in Figure 2. This is what a planner would work on for a 12-month plan. The space was constructed by using Simon's problem solving model (Simon 76) and was confirmed by the real world planners. Figure 3 indicates a process for one node in the problem space. Each of the nodes should have a similar process. The processes are the application of the visualization procedure depicted in Figure 1 in Section 3. Figures 4 and 5 show the production planning raw data and result data in the tabular form, as provided by most MRP II like systems. Formula (1) to (3) in Table 1 show how the indicators are calculated. These indicators aggregate the large volume data into meaningful insight for decision-making purposes. The final visual images, as shown in Figures 6-9, are constructed by using the specially designed image construction rules (Zhang 1995, Zhang 1998).

Figure 2. Production Planning Problem Space

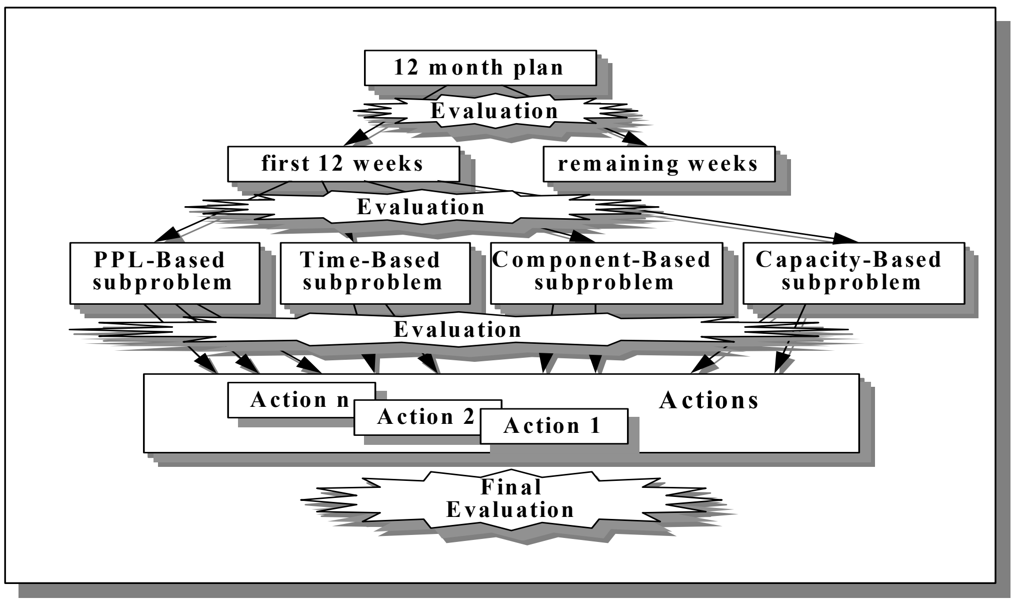


Figure 3. Visualization Procedure for Production Planning Support

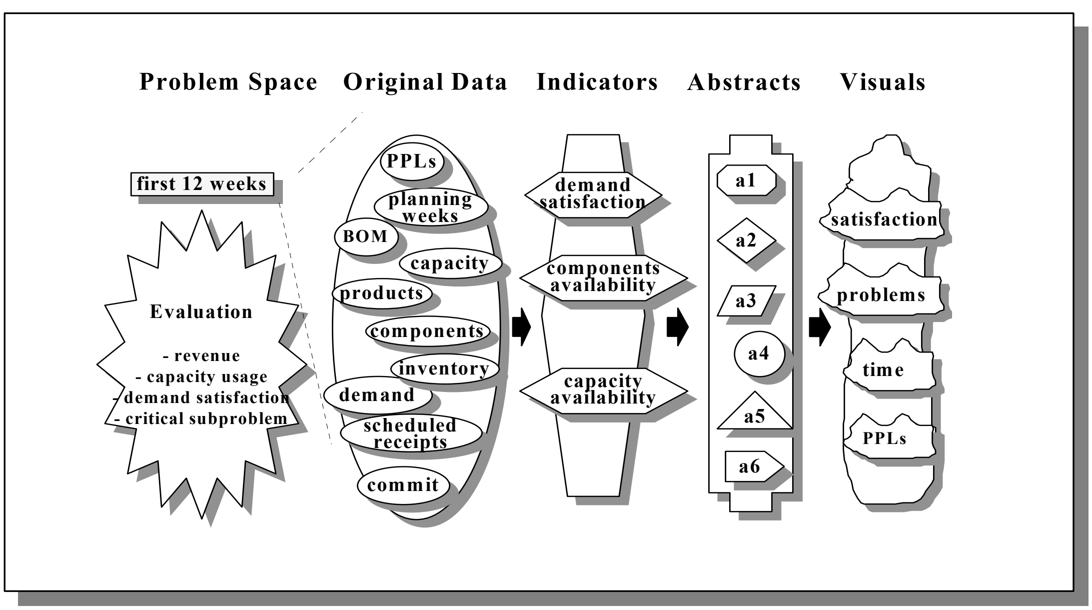


Figure 4. Planning raw data

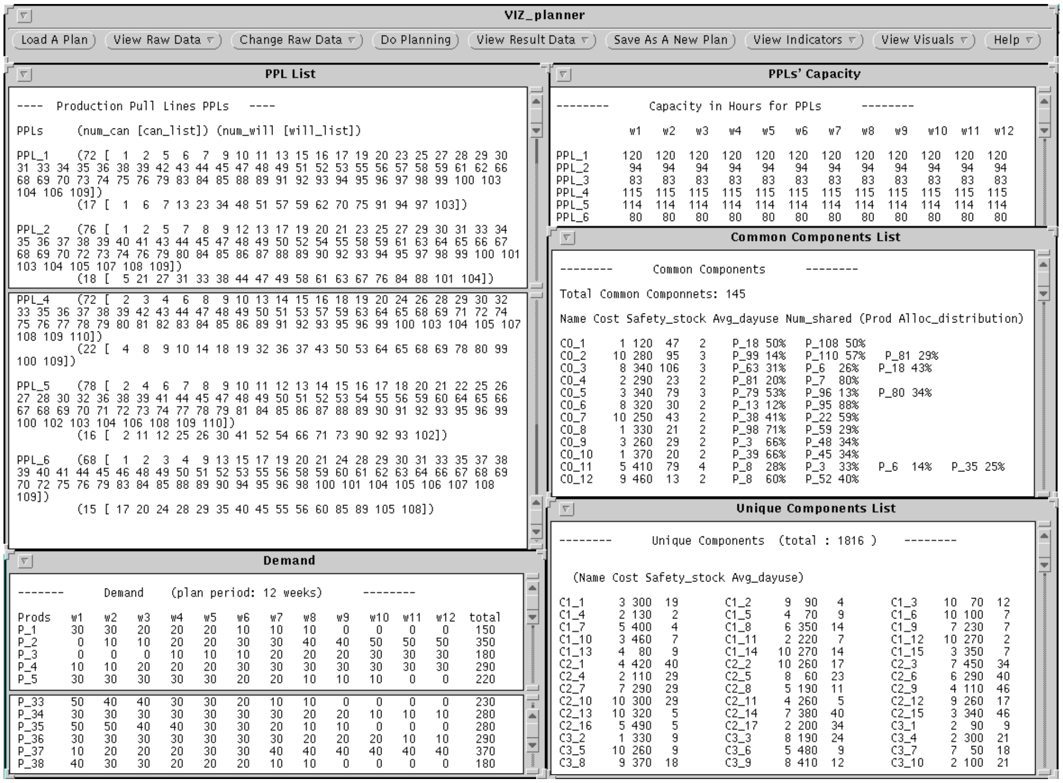


Figure 5. Planning result data

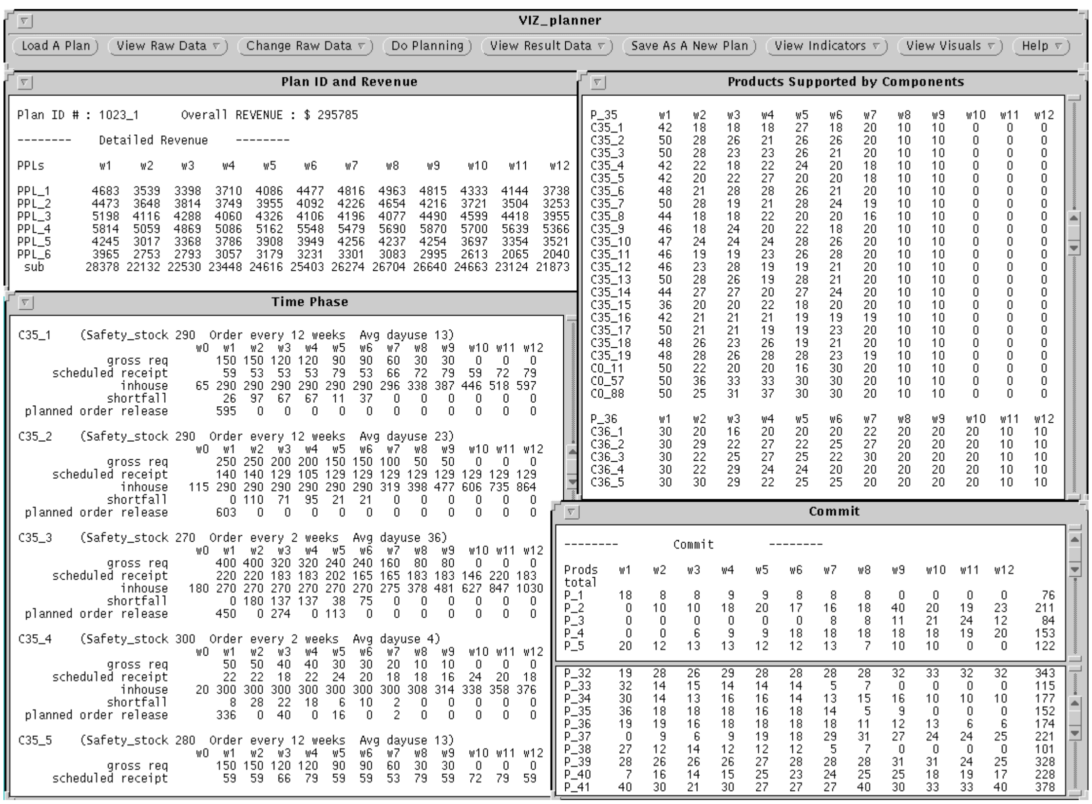


Table 1. Data aggregation formula

Demand Satisfaction Indicators

$$\underline{D}_{Lk} = \frac{\sum_{n=1}^{N_L} f_n \bullet P_{kn}}{\sum_{n=1}^{N_L} f_n \bullet D_{kn}} \bullet 100 \qquad 1 \le L \le 6 \tag{1}$$

$\underline{D}_{Lk}$ is the demand indicator for PPL L at week k;
N_L the number of different products produced by PPL L;
f_n the profit (in dollar) of product n;
D_{kn} the required production quantity for product n at week k;
P_{kn} the actual quantity of product n based on available capacity and components.

Component Availability Indicators

$$\underline{C}_{Lk} = \frac{\sum_{m=1}^{M_L} (R_{km} - S_{km})}{\sum_{m=1}^{M_L} R_{km}} \bullet 100 \qquad 1 \le L \le 6 \tag{2}$$

$\underline{C}_{Lk}$ is the component indicator for PPL L at week k;
M_L: # of different components after decomposing N_L products produced by PPL L;
R_{km} the required quantity for component m at week k;
S_{km} the shorten quantity of component m at week k.

Capacity Availability Indicators

$$U_{Lk} = \frac{\sum_{n=1}^{N_L} D_{kn} \bullet T_n}{H_{Lk} \bullet 60} \bullet 100 \qquad 1 \le L \le 6 \tag{3}$$

U_{Lk} is the utilization for PPL L at week k;
N_L the number of different products produced by PPL L;
D_{kn} is the required quantity for product n at week k;
T_n is the average minutes required for producing a single unit of product n;
H_{Lk} is the available hours for PPL L at week k.

Figures 6-9, along with Figures 4 and 5, represent a planning problem that considers 110 products, 1961 total components with 145 common components, 12 planning weeks, six assembly lines (or PPLs), and two production constraints: tool capacity and components.

Figure 4 shows some of the typical raw data a planner has to consider. The *PPL List* shows the products each production pull line can produce and the actual distribution of products over the PPLs during the planning period. When a planner is thinking of moving the demand of a product from one PPL to another, s/he needs to refer to this list to find out whether the other PPL can produce the product. For example, product P_35 will be produced by PPL_6, although PPLs 1, 2, and 4 can also produce it. If necessary, P_35 can be moved from PPL_6 to PPL_1 because PPL_1 has the ability to produce it. The *PPL's Capacity* lists the capacity in hours of machine usage for each planning week. These data can be quite dynamic and flexible: the hours can increase (when adding a machine) or decrease (when one machine breaks down or is moved to another PPL). The *Demand* indicates the quantity of each product that is required for each planning week. For example, product P_35 should be produced in the quantity of 50 for week 1, 50 for week 2, etc. The Demand window is split into two parts to show product P_1 through product P_110. The *Unique Components List* displays the name or identification of each of the 1816 unique components (product P_1 uses C1_1, C1_2, … C1_n), cost, safety stock, and average dayuse. For the common components, the *Common Components List* displays additional information (e.g. the number of products that use the common components and a list of these products with initial allocation distribution). For example, among 100 available common component C0_4s, 20 will be used by P_81 and 80 by P_7. A planner in search of a superior plan can change this allocation during the planning process. Other raw data that are not shown include *Inventory*, *Scheduled Receipts*, and *BOM*. The *Inventory* file shows the available number of components before planning. *Scheduled Receipts* indicates the promised quantity from the suppliers for each planning week. *BOM* (Bill Of Materials) is a standard production document and indicates how many components each product needs during production. Some of the raw data, such as Demand, Capacity, Scheduled Receipts, allocation of products over PPLs, and allocation of common components over products, can be changed during the planning period.

Figure 5 lists some of the planning result data in tabular format. The *Plan ID and Revenue* shows the plan ID and the overall and detailed revenue figures of a particular plan. In this example, we consider the overall revenue to be the planning objective: the higher the revenue, the better the plan. *Time Phase* is a typical result of the MRP II type of planning process. Time phase is detailed to each individual component in terms of the potential requirement, availability, and ordering plans. Time Phase data are difficult to use, owing to the critical components. That is, not all shortfall components should be ordered as suggested by Time Phase data (see below). *Product Supported by Components* shows the supported quantity of each of the needed components of each of the products. Because the components have to be in sets in order to produce a product, the minimum number of all the supporting quantity will be the actual number of the product that can be produced. The component with the minimum supporting number is thus regarded as a critical component. For example, for product P_35 in week 1, only 36 P_35s can be produced, owing to the availability of C35_15 (can only support 36 P_150) regardless of how many other components are available. C35_15 thus is a critical component for P_35. If a planner cannot solve this component's problem, then it is useless to solve other shortfall components for this product. Because there are so many products and so many components, it is very difficult to identify the critical components just by examining this huge data table. The *Commit* file shows the quantity of each product that can be produced for each planning week, dependent upon the available components and capacity. This quantity is always less than or equal to that in the Demand file, which shows the required quantity. Other result data not shown include *Capacity Utilization*, which shows the proportion of required hours to available hours.

At a global level, a planner is concerned with how much demand can be satisfied according to component and capacity constraints. This concern can be addressed by two images that complement each other: Global Satisfaction & Potential, which shows the satisfactory side of the planning problem, and Global

Shortfall, which indicates the shortfall side. Both images focus on the relationship among demand, capacity, and component. These three data objects must be placed in a certain PPL and for a certain planning week. Thus there are five data objects in these two images. Figure 6 is the Global Shortfall view that shows demand shortfalls based on capacity and component shortfalls for each PPL during each planning week. The longer the bar, the higher the value, which is standardized to ensure that all data values can be represented by the image, and to allow planners to make relative comparisons. Notice the consistent capacity shortfall for PPLs 3 and 4. This implies several possible global solutions: either re-assign production loads among PPLs, or re-allocate production capacity to reduce capacity shortfall for these two PPLs.

Once a planner has some idea about the global status of a plan, s/he may want to find out the satisfaction status for products, because demand satisfaction is determined by product satisfaction. Figure 7 lists all the products in terms of their production satisfaction (line bars) in the context of demand satisfaction (area bars). Demand Satisfaction is dependent on Product Satisfaction for each PPL in each planning week. This image allows micro/macro readings (Tufte 1990) of products (line bars) and corresponding demand satisfaction (area bars). For PPL6 at week 3, for example, a correspondence can be found between the group bars of products' satisfaction in this PPL and the bar for demand satisfaction (about half-way satisfied). A planner's focus can be on demand (macro) or products (micro). The bars along the product dimension but with a lighter color from that for product (or component as in Figure 9) mean that there is no demand for those products in those weeks. Thus the value for satisfaction is always 100% (or 0 for shortfall value).

Next, the planner may want to focus on a specific PPL to learn more about satisfaction status for products in that PPL. In Figure 8, a detailed image of Product Satisfaction for a specific PPL is zoomed in from Figure 7. Each product is identified by its identification number and can be examined individually. For example, the image shows that product P_35 has problems (the bars are not as high as 100%) for all the weeks except the last three, where there is no demand on production of this product. A future detailed analysis maybe necessary to find out why P_35 has problems.

If a particular product is of great interest to the planner, s/he will want to know more about what causes problems for the production of this product. In production, all the required components have to be in sets in order to produce one product. Figure 9 can provide a detailed view of which component of this product is most lacking and thus affects the production of this product. The underlined components at the right of the image are common components and are used by multiple products. This image indicates to the planner that s/he should resolve the components with the shortest bars before s/he puts any effort on any other shortfall components. For example, at week 2, although all the components are short for P_35, the image shows that components 1, 8 and 9 (the shortest bars) are among the critical components and should be resolved first before planners trying to resolve problems with other components. Similar to those in Figure 8, the lighter colored bars mean there is no demand for Product 35 in weeks 10, 11, and 12.

5 CONCLUSIONS

The general visualization model in Figure 1 guides the development of a visualization prototype. Prototyping is an iterative process with formative evaluations occurred during the development of the prototype system. Once the prototype system is finished, a usability study is necessary to ensure that the visualization system is effective and efficient in supporting human problem solving. There is also an issue of testing the system with simulated data (Zhang & Pick 1998). Very often the real data sets are not available when the prototype needs to be tested. How to generate simulation data representative of the real data sets is not a trivial question.

As in the development of any information system, the development of business information visualization systems is a balance between science and art. There is always a part that requires a craftsman's skills and intuition. There is, however, a hope and a possibility that the development procedure can have software engineering type of guidelines. This is the intent of this paper. Although a particular BIV is domain specific, the development methodology and many techniques or methods can be domain independent. An important component in this methodology is a human centered perspective, rather than technology centered.

Business Information Visualization as a new field has just begun, but has a great potential to enhance human decision-making processes. With more BIV systems constructed and applied, a methodology becomes significant in guiding research and practice, and for developing automated toolkits to build innovative and domain-specific business information visualizations.

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Figure 6. Global shortfall view

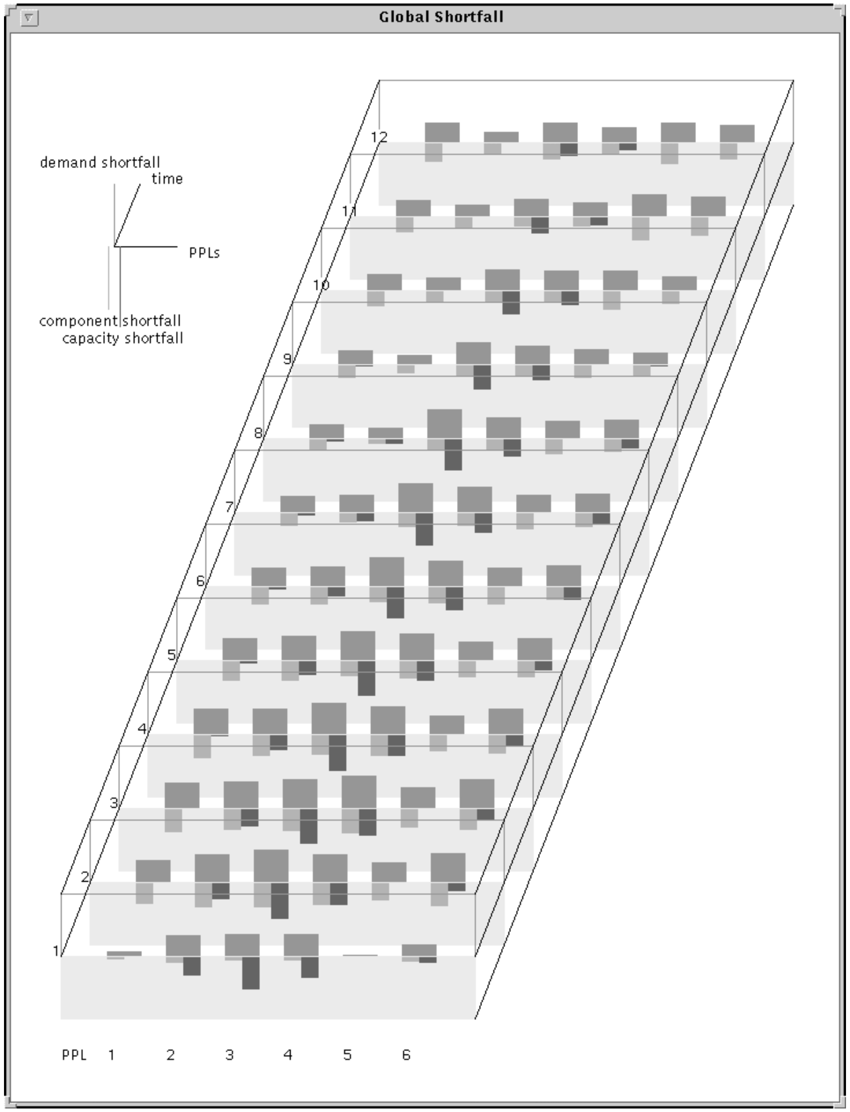

Figure 7. Global product satisfaction

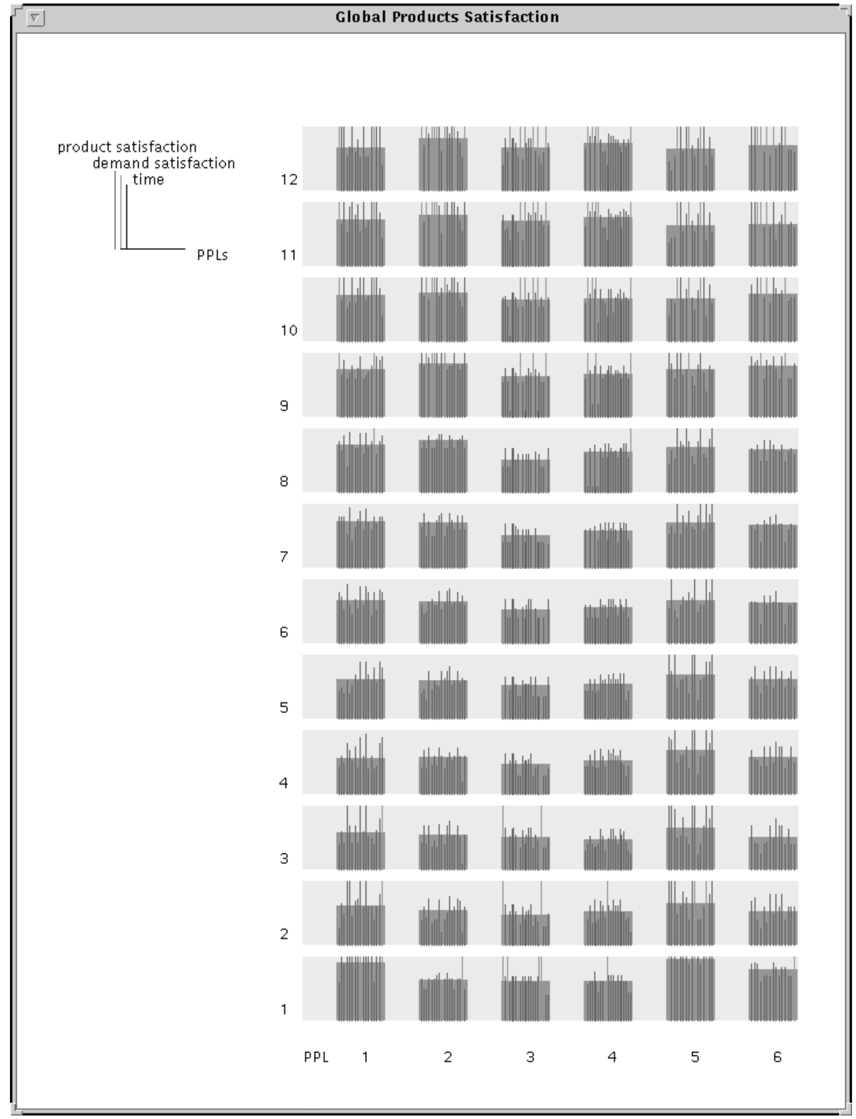

Figure 8. Products satisfaction by PPL

Figure 9. Product supported by components