Visualization Blackboard

Visualizing Production Planning Data

Visualization of production planning data for decision making in manufacturing is nearly nonexistent. The planning problems at the Electronic Card Assembly and Test plant (ECAT) at IBM Austin, Texas, prompted the research project reported here. The project studied the characteristics of this type of managerial data, then developed special visualization techniques for constructing visual representations to support planners in developing superior production plans. A visualization prototype called VIZ_planner was designed, implemented, and empirically evaluated in a lab setting. Using this tool, hundreds of products, thousands of components, and many other factors can be visualized to provide planners with production planning insight.

Production planning data

In manufacturing production planning, a planner’s goal is to maximize overall revenue from production, subject to resource constraints such as tools and component availability. A typical manufacturer can have hundreds of different products and thousands of different components. Some of the components are used by different products and thus named “common components.” Different production assembly lines (also called production pull lines, or PPLs) share tool capacity and components during production.

A production plan covers several weeks and is done every month. The decision-making environment is usually very dynamic. Often a severe component shortage problem exists. Most of the shortfall components can be obtained quickly by negotiating with suppliers. Among all the short components, however, only a very few are “critical” or bottleneck components.

During planning, the planner has many possible actions to take in solving some of the problems or subproblems. For instance, the planner can move products to different assembly lines, move products to different time periods, change an assembly line’s capacity, change the quantity of products made (demand), change the quantity of components available (scheduled receipts), and change the distribution of components over products (production mix). In such a dynamic environment, the planner’s understanding of the problems is crucial.

Because of complicated relationships among data and the dynamic nature of the decision-making environment, existing production planning systems (such as MRP II and simulation systems) cannot provide solutions that reflect the changing constraints and environment. Although some of these systems have friendly user interfaces and simple one- or two-dimensional graphs such as line charts, bar charts, pie charts, and so on, the data they can provide are basically tabular—either limited to the size a computer screen can handle, or on a printed report up to several hundred pages long. These data could not give planners a clear vision of the overall perspective. In other words, they show trees but not the forest. Planners must use their cognitive powers to figure out the “stories” behind the data, including identifying critical components among all the shortfall components.

Computer-generated visualizations shift some of the planners’ mental load to their perceptual systems, enhancing the process. On the other hand, production planning data are voluminous and multidimensional, and have complicated interrelationships (not linear, hierarchical, network, or geographical). These data are not geometric by nature. Nor is there an obvious geometry to assign to each data object involved or obvious geometry indicating the relationships among the data objects. This provides a great challenge for information visualization.

In our approach to visualizing the nonvisual, we first designed “visual abstracts” for each data object involved in the decision-making process. Then we constructed images that geometrically linked multiple data objects.

Visual abstracts

A visual abstract basically provides a geometry for presenting a data object in a 2D plane. We intended visual abstracts to provide a foundation for (1) supporting visual perceptions and (2) constructing efficient visual representations that would facilitate all levels of interpretation. Another consideration was that the final visual representations should not be too complicated for business managers to understand and use.

According to Bertin,4 four human visual perceptions correspond to three levels of information organization. The qualitative level of information organization includes all the concepts of simple differentiation. It involves two human visual perceptions or perceptual approaches: association and differentiation. The next level is ordered, which involves all the concepts that per-
1 Image construction rules:

- Rule 1: Dependency dimensions
- Rule 2: Time-space dimensions
- Rule 3: Parallel dimensions
- Rule 4: Overlap dimensions

2 Notice the consistent capacity left over for PPL5 (blue bars), as well as late planning weeks for some other PPLs. This suggests several global solutions to the planner: either reassign production load or relocate production tools or capacity.

mit a ranking of the elements in a universally acknowledged manner. This level corresponds to ordered perception. The third level is quantitative, meaning reliance on a countable unit. It relates to quantitative perception.

We can consider Bertin’s three visual perceptions as three types of comparisons: compare to associate or differentiate, compare for more than or less than, and compare quantitatively. Traditional bar charts work well for comparisons and are well understood, including by business people. We thus extended the bars and used them as our theme for the entire visualization system. The system represents most of the values by bars—in a broader sense, such as areas or lines.

Image construction

The geometric structures indicating relationships among data objects also require careful design to be meaningful to the planners and presentable on a computer screen. An image, also called a “visual representation” or “visual” in this study, consists of elemental symbols (here, visual abstracts) and their relations. The layout of multiple data objects in one image is determined by the dependency relationships among the data objects. We say data object $A$ is dependent on $B$, or $B$ determines $A$ (fully or partially), if $A$ is a function of $B$: $A = f(B)$. In this case we say there is a dependency relationship between $A$ and $B$. In a virtual multidimensional space, each data object has its own axis, just as in ordinary one-dimensional space. The following rules, partially depicted in Figure 1, apply to data objects to make them geometrically connected.

Rule 1. Dependency dimensions: If $A$ is determined or partially determined by $B$, then $A$ and $B$ construct a 2D plane by sharing the same origin. For example, demand satisfaction ($A$) is partially determined by component availability ($B$). We call $A$ and $B$ “dependency dimensions.”

Rule 2. Time-space dimensions: If $A$ and $B$ are time series data and one-dimensional location data, and they both determine other data objects at the same time, then $A$ and $B$ construct a 2D plane by sharing the same origin. For example, it is meaningful to refer to the capacity availability ($C$) for assembly line 2 ($B$) at planning week 3 ($A$). In this construction rule, we say $A$ and $B$ construct “time-space dimensions.”

Rule 3. Parallel dimensions: If $A$ and $B$ have no dependency relationship, but they both partially determine $C$, then $A$ and $B$ could be in a parallel position sharing the same origin. For instance, component availability ($A$) and capacity availability ($B$) have no dependency relationship between them, but they both determine the demand satisfaction ($C$). We call $A$ and $B$ “parallel dimensions.” Parallel dimensions can exceed two, as long as the involved variables are independent of each other and partially determine other data objects.

Rule 4. Overlap dimensions: If $A$ and $B$ have a dependency relationship, and they are both determined by either time-space dimensions or another data object $C$,
then A and B can share the same axis (dimension) by overlapping each other. In this way, we say that A and B are "overlap dimensions"—a special case of dependency dimensions.

**Rule 5.** All elementary graphing techniques and rules, when not conflicting with the above rules, apply to up to three data objects.

**Rule 6.** Combinations of the above rules may be used to geometrically connect all the data objects involved in one image.

**Images for production planning**

Figures 2, 3, 4, and 5 depict a decision-making process that involves 100 products, 1,791 total components with 135 common components, 12 planning weeks, six assembly lines (PPLs), and two production constraints: tool capacity and components.

Figure 2 shows demand satisfaction based on capacity and component availability. It involves five data objects. Time and PPLs determine the other three data objects and thus construct time-space dimensions according to Rule 2. Demand satisfaction is partially determined by capacity leftover, as well as by component availability (Rule 1). Meanwhile, capacity leftover and component availability do not depend on each other, but they both partially determine demand satisfaction (Rule 3). Applying these rules results in the final image in Figure 2. The image can be resized in both the horizontal and vertical directions, and the angle for the entire image changes correspondingly to ensure clear reading. The longer the bar, the higher the value, which is converted as percentage information to ensure that all data values can be represented, as well as to allow planners to do relative comparisons.

Figure 3 lists all the products in terms of their production satisfaction (orange lines) in the context of demand satisfaction (green bars). Demand satisfaction depends on product satisfaction for each PPL at each planning week. This situation echoes Rule 4, where "overlap dimensions" can be applied.

In Figure 4, we have zoomed in on a detailed image of product satisfac-
tion for a specific PPL from Figure 3. Each product is identified by its identification number and can be examined clearly. The purple color means no demand for that product that week.

Suppose a specific product interests the planner—for example, Product 66. Figure 5 provides a detailed view of which component has the greatest shortfall and thus affects production. All the required components must be in sets to produce the product. The underlined components at the right are common components used by multiple products. The image shows that although during week 2 to week 6 most components are short, the planner should try to obtain the components with the shortest bars—the critical ones—before attending to any other shortfall components.

**Empirical evaluation**

We conducted an experimental lab study to evaluate the effectiveness of visualization on planners' problem-solving performance. A total of 13 motivated graduate students with production planning experience participated. To ensure that the experiment did not demand unreasonable mental effort by the subjects, we simplified the production planning tasks (decision problems) considerably. Two randomly assigned groups worked on the same decision problems using two different computer systems, respectively, within a limited time period. One system was a traditional MRP II-type system (Norm_planner) with tabular format for data displays, and the other was the simplified version of VIZ_planner called Viz_planner.

The results of the experiment indicated that

- the Viz group generated more alternatives for solutions than did the Norm group,
- the Viz group made more efficient changes in the raw data to achieve high-quality plans than did the Norm group, and
- the Viz group was more satisfied with the outcomes than was the Norm group.

Also interesting, the Viz_planner group—after learning how to use Norm_planner along with the Norm group—had only 15 minutes to watch the Viz_planner demonstration and 40 minutes to practice with it. Their success in using the program with so little training led us to conclude that the final visual representations for manufacturing production planning are easy to understand and use.

**Conclusion**

Our project tested the feasibility of visualizing large amounts of managerial data to support decision making in manufacturing production planning. The results look very promising. Although we chose a specific management domain for the study, our ultimate goal is to discover rules of information visualization that can be applied in many management domains. Future research includes refining and applying the visualization techniques to other managerial domains and conducting more extensive empirical evaluations.

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**References**


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