

## Finite Planning Models through Computer Animation

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"...the universe...is written in the language of mathematics and its characters are triangles, circles, and other geometrical figures." (Galileo, 1564-1642)

The world knows two powerful information-processing systems, the human mind and the digital computer. What separates the two is the display of information. Graphical interfaces bridge the gap between mind and computer. The mind has parallel processing abilities unrivaled in nature. The computer has computational speed. Properly harnessed, the mind and the computer form a powerful unit. This synergy leads to greater cognition and better decisions in business.

Galileo alone with his gaze into the night found new worlds. Through the telescope, his eyes and mind took hold of the shapes and patterns that occupy the sky. He further rendered his insight into a new science. By studying graphical interfaces, we, like Galileo, can explore new worlds of information. We can also develop our insight into a science.

At the 1998 APICS International Conference, we spoke of visualization and its application to finite capacity planning (FCP) [21]. Today, another closely related topic occupies our minds. We speak of computer animation and FCP. Animation has a long history of use in the simulation of physical systems. Although its application to FCP models remains limited, we feel it can become a useful tool. Animation opens a new way to explain the behavior of dynamic systems. There exists a huge need for structured research in this area. It represents a field of great productivity growth in the next century.

Our interest for some years has been the analysis of capacity within the process industries. Process-oriented firms have operations that involve mixing, separating, forming, and chemical reactions. The segment includes such industries as food, chemical, pharmaceutical, plastics, paper, and biotechnology [28]. A number of process-oriented firms report problems with traditional MRP and seek alternatives [27]. They require unique systems somewhat different from those rooted in the traditional APICS body of knowledge. In many instances, planning systems in the process industries require use of mathematical models to find optimal solutions. Often it is difficult to communicate results of these models. We look to animation as a new way of strengthening the link between mind and model. It is a critical interface of future importance.

The organization of this paper is in three parts. First, we give a short overview of animation. Then we follow with a discussion of algorithm animation. Finally, we talk about the practical matter of animating the effects of forecast error.

### ANIMATION OF INFORMATION

Children of grammar-school age now create, organize, and present simple reports on topics of interest to them using computer graphics. In several New England schools, teachers have sixth graders put together seven slides in presentation format. They then ask the children to add movement to their slides. At an early age the children learn (1) the basics of verbal communication, (2) the importance of the visual, and (3) the excitement of animation. When these children become adults, they will expect computer models that give pictures of data in motion. Anything less will be inferior.

For all the current vogue about animation, there exists no consistent theory of how it improves decision-making. Even for static graphics, we know little. Cleveland and McGill note that "graphic design for data analysis and presentation is largely unscientific [4]." They study the perception of static graphics in the context of the visual decoding of quantitative and qualitative data [5]. Further, Jones [11, p. 83] states that "our

understanding of the proper use of animation is even less well-developed than our understanding of the proper use of static graphics."

The formal study of graphics and animation is a young science. It is not as old as mathematics, chemistry, or physics. In the stream of history, it is a new science that continues to gain importance as practitioners apply models.

### A BRIEF HISTORY OF GRAPHICS

The origin of modern graphics begins with William Playfair and the publication of *The Commercial and Political Atlas* in 1786 [30, p. 32]. The book contains an amazing array of graphics on British economic data. Spanning from 1983 to 1998, Tufte publishes a series of three books on the display of data [30, 31, and 32]. These books stress the importance of clear communication through graphics. They serve as a starting point for the study of static graphics and animation. Jones [11] gives a nice overview of graphics and optimization. The book contains numerous references for which we are grateful. He places emphasis on visualization.

### SCIENTIFIC VERSUS INFORMATIONAL VISUALIZATION

Understanding large sets of data is a difficult task. Scientists and engineers learn about systems by drawing pictures or using scale models. In most cases, a physical system is the object of their attention [13]. This is an example of *scientific visualization*.

In contrast, models of business problems deal with information rather than physical systems. Information has no concrete form and is not easy to visualize. Many of the models we use in practice are abstract in form. Managers sometimes struggle with the output of these models. We seek new ways managers can understand models by using graphics and animation. Some call this field of study *informational visualization*, to distinguish it from scientific visualization [11, p. 4]. By focusing on the visual aspect of information, managers can analyze data and make decisions with less detailed knowledge of the mathematics behind the models.

Good communication occurs with the transfer of the greatest number of ideas in the shortest time. This becomes difficult when dealing with multivariable problems common to FCP models. Animation promises to speed up the rate of information transfer. This improves the efficiency of decision-making.

### THE VALUE OF ANIMATION

Capacity planning in the process industries involves many variables. Seldom do these problems have clear-cut solutions. Complex exchanges take place between FCP models and users. The nature of this interaction governs the ability of planners using FCP models to find the best production plan. Animation can play an important role in understanding the workings of FCP models. It can also show the sensitivity of solutions to changes in input variables. Hence, animation will improve the productivity of FCP models in practice. It helps planners to integrate data into useful information for action.

Jones [11, p. 82] defines animation as "a special type of moving picture where each individual image or frame is carefully drawn, not photographed. Smooth motion requires between 10 to 30 images per second." In our work, we broaden Jones's definition by including any

use of graphical motion. This might include images that move at less than 10 images per second.

It is worth noting that animation differs from cinema. Animation uses pictures while the cinema uses photographs. Computer software now draws the pictures. However, in the early days animators had to draw each frame by hand. Historically, the concept of pictures in motion proved a large intellectual hurdle to overcome. In the early days of motion pictures, producers did a copyright for each frame [8]. The United States did not issue a single copyright for a film until after 1903. The feat of pictures in motion started a revolution. Never before could viewers see so much information in such a short time.

Animation gives the user different views of data. With interactive animations, the user has the ability to influence the dynamics of a system. This helps to overcome a common weakness in decision-making, the "anchor and adjust" heuristic. This type of thought pattern causes a limitation in thinking [9]. Confronted with incomplete information, planners tend to anchor with past occurrences they take as true. They then make a mental adjustment based on an assessment of new conditions. This form of decision-making leads to suboptimal solutions in supply chains [26]. Animation allows planners to look at capacity problems from different points of view. It limits the impact of the anchor and adjust heuristic on decision making.

A final value of animation involves learning and recall. Evidence exists that animation helps people to remember what they have learned more easily [11, p. 95] and [15, 16, 17, 18]. Some think the process of learning may be just a case of pattern recognition. Herbert Simon, a great scholar of cognition, believes pattern recognition is a critical part of thinking [19]. If planners learn relevant patterns, and have the ability of recall, they will make better decisions. Animation can expose planners to a large number of different patterns. It enhances their ability to link patterns within data to cause and effect. We give an example of this later in the paper.

Currently an underdeveloped field, animation has exciting potential for practitioners. The flexibility of software allows the possibility of custom animations to meet the personal cognitive style of planners. This user-centric [24] approach will make FCP systems much more effective.

To highlight the benefits of animation, we now turn our attention to applications. For the examples given in this paper, we draw upon real data from Welch's, Inc. The data show a true picture of planning in the consumer products (CP) segment of the process industries. We also draw upon the array of models in use at Welch's over a 15-year period [1, 2, 6, 20, 22, and 23]. Most of our work involves the sensible use of computer spreadsheets in planning and we feel this a solid direction of the future. For an interesting article on the use of spreadsheets, see [33].

## ANIMATION OF ALGORITHMS

Woolsey [34] argues that useful modeling only takes place when the model builder makes results clear to nonmathematicians. If users can "see" how a model comes to a solution then the answers given from the model are more credible. Unfortunately, many models use algorithms that are hard to visualize. Animation helps users understand the behavior of algorithms.

An algorithm is a sequential or recursive procedure used to arrive at a mathematical solution. These procedures succeed when "convergence" to a single answer occurs. Perhaps the most famous algorithm is the Simplex method. It computes answers for linear programming (LP) problems. LP formulations are very flexible and a number of applications exist for production planning.

Some algorithms are very complex. Others are simple. In some cases, intricate theorems support the design of algorithms. In other cases, algorithms are heuristics that use rules in a structured way to find an answer. Heuristics do not guarantee the "optimal" answer will result. However, researchers often find heuristics that give answers close to optimal. Intensive testing is the only way to identify successful heuristics.

The published research on algorithm animation is sparse. Brown [3] provides an early book on the animation of algorithms. His work is somewhat theoretical. Other authors offer illustrations from computer science. A common example is the "sort" algorithm. Some algorithm animations are available for viewing through the Internet. Animations of sort algorithms are especially interesting to see [35].

We did a complete search for applications in operations management. Only a few papers exist. Jones and Baker [10] publish an interesting description of MIMI/G (finite planning software). MIMI/G allows users to model their planning and scheduling problems graphically. However, the article deals only with animation of model outputs. To our knowledge, no published research exists on the animation of algorithms for FCP.

## THE ANIMATION OF FCP

As one can imagine, describing animation is a difficult task. Our first attempt involves a heuristic for FCP used at Welch's [2]. A single principle guides our thinking about algorithm animation. We focus on "interesting" events that occur as part of the heuristic. These events might include a particular step in the solution method that is critical for success of the algorithm.

The heuristic we animate deals with a single-stage FCP problem. Given capacity constraints we must find a feasible production plan. As a criterion of success, we use the cost of setups and inventory. Finding the production plan that minimizes cost while meeting capacity is our goal. To accomplish this we use the proven Silver-Meal [25] method for lot sizing. The method finds the lot size that offers the least total cost considering setup (fixed) and inventory (variable) cost. It does so by averaging the costs (setup and inventory) for each forward period that a chosen lot size spans and stopping when costs start to increase. With this method, lot sizes are increased in one period quantities. The resulting lot size represents a near optimal trade-off between setup and carrying costs.

The Silver-Meal heuristic does not consider capacity in making lot-sizing decisions. Dixon and Silver [7] improve upon this method by adding capacity limits. We make further improvements by adding setup time to the heuristic. We also code the heuristic in visual basic with a spreadsheet interface. The following provides an overview of the procedure:

1. Preliminaries:
  - Prepare the forecast by netting out beginning inventory.
  - Incorporate safety stocks into demand forecasts.
2. Determine feasibility requirements for each period:
  - The required production in each period, over and above immediate demand, to prevent infeasibilities in future periods.
3. For each period:
  - Satisfy immediate demands.
  - Economically satisfy feasibility requirements by backshifting full or part lots.
  - If capacity remains, economically backshift full or part lots.
4. Look for improvements.
5. Report schedule and costs.

The first two steps of the procedure are simple tasks. These activities serve a preparatory purpose. However, "interesting" events occur in steps 3 and 4. In these steps the heuristic computes lot sizes for each item, then shifts full or partial lots to reduce cost within capacity limits. The lot size depends on the marginal cost savings per unit of capacity consumed for future demand. Those items with greatest marginal cost savings are candidates for shifting to an earlier time (fulfilling feasibility requirements). Upon meeting feasibility requirements for the span, the heuristic looks for improvements by searching for economic transfers forward in time.

For simple FCP problems, we can animate the events of steps 3 and 4. This allows users the ability to see how lot sizing and shifting takes place. By seeing the animation, users develop a deeper understanding of how the heuristic works. We feel this understanding translates into better

Figure 1.

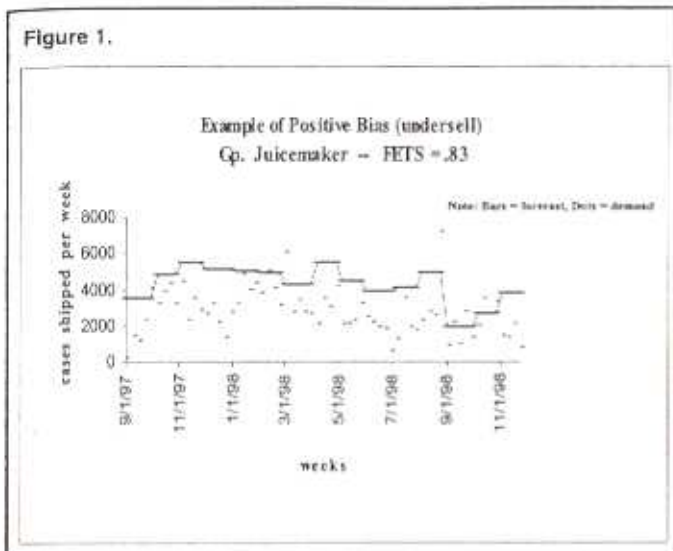


Figure 2.

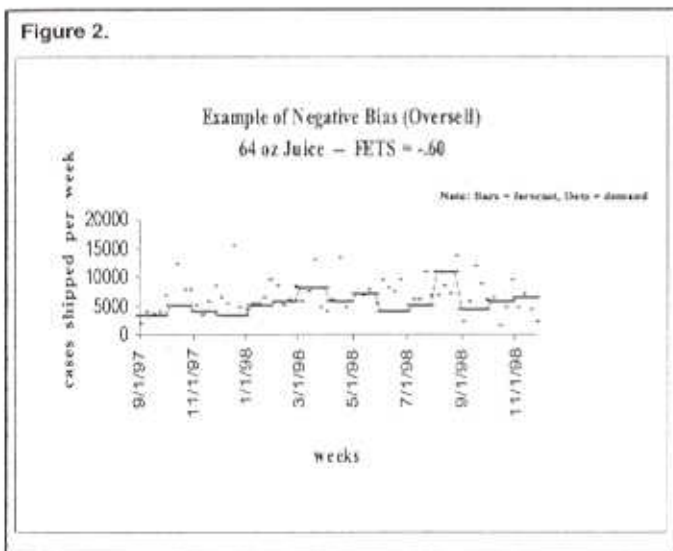
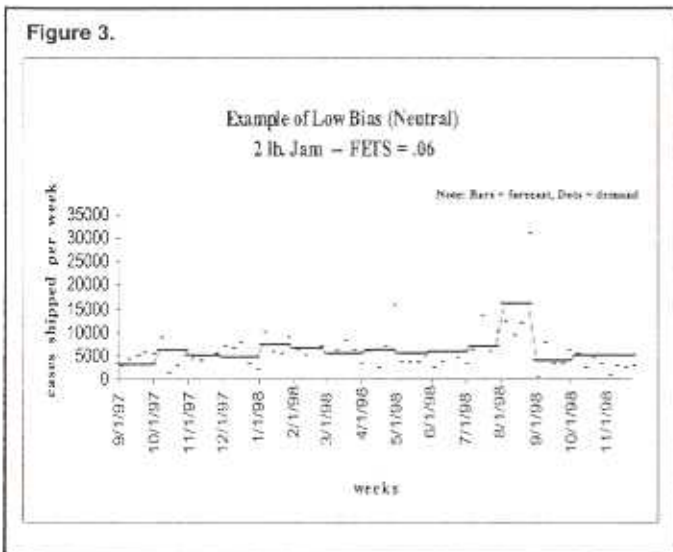


Figure 3.



planning. Decision-making with marginal cost savings is an important skill to learn. It has applications to areas beyond FCP.

We choose two-dimensional animation software for this FCP problem. There are several different ways to present the animation. Space limitations prevent us from publishing full details. However, we will show the animation as part of our presentation in New Orleans.

We now focus our attention on the last topic of this paper, an examination of model sensitivity to inputs.

## ANIMATED SENSITIVITY ANALYSIS

Algorithm animation serves a useful long-range purpose in education. In contrast, sensitivity analysis is immediate and practical. FCP models require adjustment of input parameters to gauge changes in output. Animation provides a quick way to understand the relationships between inputs and outputs. Again, space limits us from publishing full details of animated sensitivity analysis. However, we can take a brief look at forecast error, safety stock, and their effect on FCP models.

## Forecast Error and Bias

Forecast error is a major obstacle for FCP to overcome. Alone, forecast error presents serious troubles for planners. However, in combination with forecast bias it is deadly. Bias occurs when forecast error follows a nonrandom course. This usually means that a forecast is consistently too high or low. We seldom find normally distributed forecast errors in CP manufacturing. In our experience, forecast error usually looks like figure 1 (data from Welch's).

Figure 1 compares actual versus forecast shipments for a specific product (65-week period). Actual demand tends to be lower than the forecast. During the entire period, actual exceeds the forecast only 8 times (12 percent). The strength of the relationship is quite dramatic. It is common that we forecast too high. A consistent undersell of the forecast results.

We can measure the intensity of forecast bias by calculating the Forecast Error Tracking Signal (FETS, see Appendix). A FETS value between 0 and 1 indicates the tendency to undersell. A value between 0 and -1 indicates an oversell. Values close to 0 means errors are random.

For figure 1, the FETS is .83. This means a strong undersell tendency exists. As long as there is no change in the "process" of forecasting we assume the trend will continue into the future.

At times bias is negative (oversell). Figure 2 is an example. About two-thirds of the time this product sells more than the forecast. For figure 2, the FETS is -.60.

Finally, we observe a rare case of neutral bias. Figure 3 shows an example where the FETS is .06, almost neutral. Note the spike in demand about 9/1/98. This date represents the end of Welch's fiscal year.

Another tracking signal for bias is the Trigg [29] method (see Appendix). Though rare in application, it identifies forecasts where the spread of errors is nonrandom. A value greater than .51 for T means the forecast has bias. For the figure T is

|          | Value of T |
|----------|------------|
| Figure 1 | .70        |
| Figure 2 | .18        |
| Figure 3 | .47        |

The exception is figure 2. It seems to show negative bias (oversell) but the value of T is under .51. As it turns out, the value of T exceeds .8 for much of the time. However, toward the end of the time series, the forecast errors trend toward an unbiased pattern. This influences the value of T to a lower number. Therefore, in using the Trigg method it is important to see how it changes over time. We find that planners have a hard time making this visualization. Animation provides a huge aid to understand forecast bias.

For both the FETS and T we build simple animations that show how the coefficients change with changes in the pattern of forecast error. A table of bias indicators presents a powerful display of forecast performance. We can see the impact upon safety stock. However, if planners do not have a mental image of bias indicators, the tables are useless. Animation provides a way for planners to learn the meaning of the calculations. They link a mental image of the pattern of errors to a bias coefficient. Animation is an effective tool in this regard.

### Forecast Error, Bias, and Safety Stock

We can incorporate bias calculations into safety stock planning.

The usual methods assume a normal distribution of forecast errors. If we apply common methods to situations where strong forecast bias exists, we will overstate safety stock. A high safety stock means greater requirements for production. With FCP, greater production might cause a non feasible situation. If this develops because of overstated safety stock requirements, it causes confusion. During our years of experience, we rank forecast bias as a major cause of FCP failure.

In 1984 Welch's began a new way of doing the safety stock calculation that accounts for forecast bias. We adapted the method put forth by Krupp, see [12, 20]. This offers a more rational way of setting safety stock levels. In many situations FCP models use a "days of supply" value for safety stock. Users input the value into FCP models. The weakness of this approach is that it gives no weight to forecast bias. There also is no statistical link to service levels. An improper safety stock level often affects production timing, lot sizing, and sequencing. Under FCP, the effects of poor safety stock planning are major.

Our approach includes service levels (see Appendix for calculations). This is an important input. By varying the service level, we see the relationship between inventory investment and customer service. This is of great value to CP manufacturers.

We did a study on how much savings result by decreasing inventory levels. Using a deterministic simulation, we find a decrease in service of 1 percent saves \$180,000 in carrying costs. This allows for an objective view of the value of inventory. Because of the study, we did not lower service levels, thinking the cost savings not worth the offset to our reputation with customers.

By including dynamic safety stocks, we can animate the effects of forecast error and bias within a FCP model. This gives the user a powerful tool to visualize the trade-off between cost, service, and capacity. Typically, we change one parameter rapidly and show the effect on outputs. We use different shapes that change in size to symbolize cost and capacity utilization. Our approach parallels the work of Jones and Baker [10].

### CONCLUSION

Animation provides a new way to view information. It is an active method that leads to understanding of systems dynamics. We feel animation has great application to FCP models. At Welch's we experiment with simple forms of animation and find it useful. In the future, FCP models may include animation of algorithms and sensitivity analysis as standard features.

### APPENDIX

We list a summary of the important calculations for safety stock planning:

$$\text{Safety Stock} = (S) \times (k) \times (\text{TICF}) \times (u) \times (t)$$

Where:

$u$  = forecast demand per day

$t$  = lead time

$k$  = service level multiplier

$s$  = suppression factor (straight line) =  $1 - \text{FETS}$

For the Forecast Error Tracking Signal (FETS):

$$\text{FETS} = \sum_{i=1}^n (u(i) - x(i)) / u(i) / \text{TICF}$$

For the Time Increment Contingency Factor (TICF):

$$\text{TICF} = \sum_{i=1}^n |u(i) - x(i)| / u(i) / n$$

$u(i)$  = past weekly demands

$x(i)$  = past actual weekly sales

$n$  = number of periods

### Discussion of the Safety Stock Calculation Method

Lead-time ( $t$ ) represents the amount of "hold time" for a product. We choose to use just the hold time and not the entire manufacturing lead-time for a specific reason. If we assume the SS placed into a FCP will represent the minimum amount of inventory needed at the end of a week for a product, then the FCP model should plan production (timing) to meet that minimum inventory level. If there is not enough capacity available, the FCP model will advance production.

### The Formula for a Tracking Signal Developed by Trigg

$$E(t) = \beta e(t) + (1 - \beta)E(t-1)$$

$$M(t) = \beta |e(t)| + (1 - \beta)M(t-1)$$

$$T(t) = |E(t) / M(t)|$$

Note:  $e(t)$  is the observed error in period  $t$ .  $E$  is smoothed error and  $M$  is the smoothed absolute error.

If forecast error is unbiased, then  $E(t)$  should be small compared to  $M(t)$ . Trigg claims that  $T > .51$  indicates nonrandom errors for beta of .1 [14, p. 89].

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