E-16

Improved Supply Chain Management through Mathematical Modeling: A Process Industry Case Study

Edmund W. Schuster, CPIM, CIRM

Moving goods from plants to customers entails an intricate web of decisions. Each decision must be effective for ongoing business success. With thousands of such decisions made each day, the role of model building becomes more important.

In the process industries, logistical costs equal a high percentage of sales revenue. Logistics also affects customer service levels in meaningful ways. Many firms use customer service as a tool to combat competition. Models improve decision making about customer service levels and cost.

We study the supply chain for improvement opportunities using models. Our work occurs through the Center for Process Manufacturing, located on the campus of Penn State Erie. The Center is a partnership among APICS, Penn State Erie and Industry. This arrangement allows ideas about model building to flow from the university into application. APICS plays an important part in providing forums to discuss studies conducted by the Center.

This article is a product of applied research and practical experience. We focus on links between customers and suppliers typical of the process industries. With examples from Welch's, Inc., we examine the nature of continuous replenishment planning (CRP) systems in supply chain management (SCM). These systems are gaining wide spread use in the consumer goods segment of the process industries. Many authors tout the virtues of building partnerships and SCM. These articles often deal with the use of information technology to gain competitive advantage. However, few mention specifics [as examples see Bowersox, 1990; Fuller, O'Connor and Rawlinson, 1993; Malone, Yates and Benjamin, 1989; Pine, Victor and Boynton, 1993; Stalk, Evans and Shulman, 1992].

In this article we begin with a review of related literature on SCM. Then we continue with a discussion of SCM structure. Next, attention shifts to specific parts of the supply chain, including forecasting, automatic re-order methods, truck loading schema, finite planning methods and material requirements planning. Finally, we conclude with a survey of new thinking about supply chains.

RECORD OF COGNATE RESEARCH

The problem we wish to explore involves SCM for consumer goods companies. This segment of the process industries meets with steep expectations for customer service. This imposes the need to maintain safety stocks that reflect dynamic demand, forecast error and bias, manufacturing lead time and hold time [Allen and Schuster, 1994]. In addition, process-oriented firms must respect capacity limits on production. With the arrival of electronic data interchange (EDI) technology, customers also expect suppliers to maintain inventory levels using CRP systems. All of this combines to impose a formidable problem in inventory management and cost control.

Flow between plants and customers is seldom even. It is characterized by fits and starts, and rapid changes. In this sense, the flows represent a dynamic problem.

For the importance of this problem, the literature shows a lack of specific solutions. Most writing concentrates in three areas: 1) the value chain, 2) apparel manufacturing, and quick response with overseas suppliers, and 3) cost and service trade-offs using internal planning systems.

A host of articles explore the value chain. Most of this work finds its origin in a single author [Porter, 1985]. Others report on the analysis of value chain using mathematical programs run on microcomputers [Shapiro, Singhal and Wagner, 1993]. Several have applied these ideas at large computer firms [Arntzen, Brown, Harrison and Trafton, 1995; Lee and Billington, 1993; Lee and Billington, 1995]. Some look beyond operational issues toward strategic use of information in value chains [Rayport and Sviokla, 1995].

Although these authors make important contributions to cost reduction, they do not capture the essence of dynamic demand situations. Most of the work appears oriented toward static analysis of networks.

The 1995 APICS International conference featured a track on quick response. Several papers are worth mention. Perry and Ross [1995] outline the basics of CRP in the context of efficient customer response (ECR). Ross [1995] shows examples of "auto replenishment" between customers and suppliers. Martin and Landvater [1995] offer a perspective of ECR. APICS has also published several other articles on supply chain management [see Cook and Rogowski, 1996; Hammel and Kopczak, 1993; Park, 1994].

Apparel manufacturers took early steps in SCM. With long lead times and short product life cycles, apparel manufacturers found great need to manage the supply chain. Several articles provide general perspective as well as detailed analysis [Fisher, Hammond, Obermeyer and Raman, 1994; Fisher and Raman, 1996].

In several manufacturing situations, authors report cost savings and improved customer service [Flowers, 1993; Pooley, 1994; Robinson, Gao and Muggenborg, 1993]. In some cases cost savings are impressive [Taube, 1996].

All the articles cited are of similar ilk. They address important SCM problems in the static sense. However, they offer little insight to dynamic problems experienced by CRP systems. None of the articles reviewed covered the precise problem we investigate. We now turn attention to an SCM framework for consumer goods manufacturers.

THE SUPPLY CHAIN MODEL

One fact of supply chains is that uncertainty in demand causes dynamic inventory swings [Buzzell, Quelch and Salmon, 1990]. These swings are often dramatic. Though swings are easily modeled [see Sterman, 1992], it is not as simple to prevent them from occurring. One way to prevent swings involves minimizing deviations within the supply chain. This dampens swings.

Our intent is to build an SCM system that takes every opportunity to minimize deviations. Some examples of things that cause deviations include forecast error and bias, and uncertain lead time. Through simulation studies, we know that if production equaled customer demand, few swings occur. However, this situation is only theoretical. Practically speaking, many traps exist in the supply chain that cause swings.

Figure 1 shows a view of the supply chain system we propose. Most of the parts are common to views put forth by other authors. We add sections pertaining to CRP and truck loading.

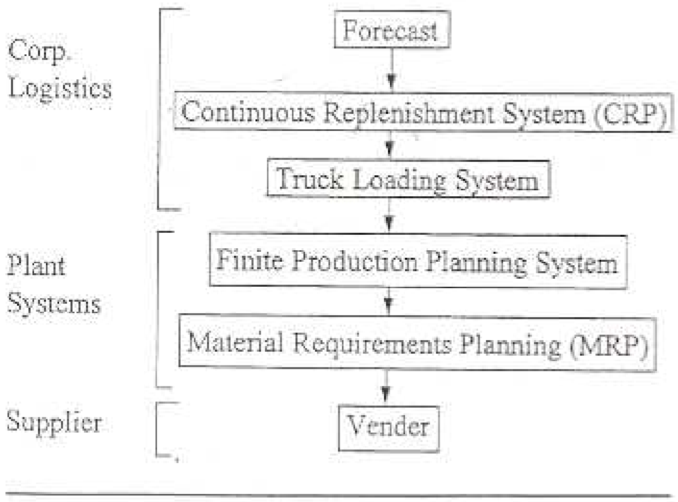
For such a system to be successful, it must "sense and respond" to changes in demand [Haeckel and Nolan, 1993]. The wise use of models provides a way of achieving this ability.

Our experience tells us that a combination of models works best in dealing with the hierarchy shown in figure 1. Other authors support this observation [Cleaves and Masch, 1996]. It is seldom we have complete knowledge of an outcome. For example, it is impossible to know demand for a product with certainty. However, we can establish the probability that a certain demand will occur. In other cases, we do know a single outcome exists with certainty. Truck loading provides an illustration. Given a set of assumptions, there is one best way to maximize weight or cube. With these examples it becomes clear that some models deal with risk and others with certainty [Davis and Olsen, p. 167]. It takes skill to blend models effectively within the supply chain.

FORECASTING CUSTOMER DEMAND

The first step in the supply chain involves forecasting. At Welch's, we receive daily data on customer warehouse withdrawals by EDI. We then produce a forecast for each customer warehouse with commercial software. This forecast drives our CRP system.

Figure 1—The Supply Chain Model



The forecasting package we use employs focused forecasting methods. It selects the best fit to past data resulting from: moving average, exponential smoothing, Holt's method and history. The model requires manual entry of parameters.

Most software developers agree with Armstrong [1984] that simple forecasting models work as well as complex models. However, as more data become available from customers, simple models may no longer give the best results. When forecast error is plotted with time for a single stock-keeping unit (SKU), the forecast shows a strong bias. The focused forecasting method used in our software did not compensate for bias. This occurs because time series methods lag the trend. In the climate of quick response, it is no longer acceptable to lag the trend. We need forecasting methods that respond to external factors not seen in historical data.

D'Itri and Schuster [1995] note a progression to more sophisticated forecasting methods that include intervention analysis for CRP systems. These methods mean use of more complex time series techniques. Box-Jenkins appears a good candidate to do forecasting for future CRP systems. Pankratz [1983] provides a solid reference on the Box-Jenkins method. Through an intricate procedure, the Box-Jenkins method can pick up subtle patterns in time series data. In the past, analysts used Box-Jenkins to predict aggregate levels of economic output. Now with improvements in computers, it can forecast individual SKU's. In some cases, analysts combine neural networks with Box-Jenkins to produce powerful forecasting systems [Sharda, 1994]

Evidence exists that firms in the retailing industry are using Box-Jenkins methods. In a recent publication, Andrews and Cunningham [1995] discuss the application of Box-Jenkins for predicting customer order levels at L.L. Bean. They use intervention analysis to account for independent variables that influence demand. This is an interesting article. It lays a base for forecasting systems that consider trade promotions.

Current forecasting methods are adequate to begin a CRP program with a customer. However, forecast error at the customer level is amplified as one progresses down the supply chain. To minimize this deviation, we must have the best forecasting system available. In the next section, we discuss the impact of poor forecasts on CRP systems.

CONTINUOUS REPLENISHMENT SYSTEMS

Once the forecast becomes available, we load it into the CRP system. At Welch's, our CRP system consists of a one cycle re-order point. When customer inventory drops below the re-order point, we must react by planning a shipment to the customer. The re-order points used by the CRP system come from manual calculations. These calculations take into account lead-time for replenishment to the customer and demand variability. Our software allows the expression of re-order points in days of forecasted demand. If the forecast has an upward trend, re-order points will also rise. In this respect, re-order points are dynamic and change with changes in the forecast.

We examine sales history to identify SKU's showing volatility. An easy way to do this involves use of the coefficient of variation (COV). The COV is the standard deviation divided by the average. If the COV is high, it means demand is volatile. Welch's grocery items (bottled juice and spreads) show a higher COV than frozen items (concentrated juice). In situations with high COV, we add several days of safety stock.

We began our first CRP implementation with a major East Coast retailer in April 1995. Since we began CRP, our total sales with this trade customer have increased; however, inventory levels show wide swings. Turn rates average an annualized 40-50 turns per year and customer service remains above 99%. In January of 1996, we had lower customer service levels as a result of sharply increasing sales. Our forecasting system did not respond quickly enough to the rise in sales. After adjustments, service climbed above 99% in March.

Despite satisfactory results from our CRP system, we believe improvement is possible. First, our software handles only one cycle for re-order. It is not a typical distribution requirements planning (DRP) system with time phased future orders [see Martin, 1983]. To integrate CRP into master scheduling systems that drive plant production, there must be time-phased orders spanning several months into the future. Some software packages have this capability. In several cases software firms customized existing DRP packages to accommodate individual customers in a CRP mode.

Second, CRP systems must use better methods to plan safety stock. Dynamic buffer stocks used by CRP systems should account for forecast bias. Proven methods exist to accomplish this [see Schuster and Finch, 1990]. More effective buffer stock planning will absorb some forecast uncertainty. This provides a great benefit to the master scheduling process for plant operations.

Finally, CRP systems need to insure even run-outs for every SKU in a customer warehouse. This is an important issue because demand is seldom great enough to ship a single item per replenishment order. If run-outs are uneven, a chance exists that a single SKU will need replenishment while other SKU's have enough inventory. This forces a difficult question. One can either let a single SKU go out of stock, or ship orders consisting of several SKU's causing increased inventory at the trade customer's warehouse.

The control of run-outs depends on demand for each item and the size of orders shipped from plants to customers. In the next section, we turn our attention to control of run-outs, loading of trucks and plant warehouse efficiency.

THE TRUCK LOADING PROBLEM

Control of run-outs at customer warehouses minimizes deviations in the supply chain and adds to cost savings. At Welch's, our CRP software has a module to load trucks as SKU's reach re-order points. However, we often experience uneven run-outs and air weight when the CRP software loads trucks automatically. We believe the CRP software uses a heuristic procedure to load trucks. The heuristic breaks down under certain conditions.

We now present an improved procedure to load trucks and to control run-outs. This procedure is not yet part of our CRP process. It has the added advantage of loading trucks in such a way as to increase efficiency at our plant warehouses. For the following example, we use a customer that has enough volume to justify truck load (44,500 pounds) orders.

Truck Loading Procedure

Objective: Load trucks so that 1) air weight is minimized, 2) an even run-out occurs for all products at the customer's warehouse and 3) plant warehouse efficiency is increased by loading pallets with even layers of SKU's.

Step 1. When a single SKU at a customer warehouse drops below its re-order point, start procedure.

Step 2. For each SKU in the customer's warehouse, net existing inventory from the daily demand forecast.

Step 3. After netting out inventory, convert into weight per day for each SKU.

Step 4. Sum the weight per day for all SKU's to get a total weight per day.

Step 5. Calculate the cumulative weight per day. When cumulative weight per day is just shy of a full truck load, stop.

Step 6. Solve the following integer program (IP):

Max $S_i\, w(i)x(i)$ [1]

Subject to:

$w(i)x(i) \geq c(i)$, for all i [2]

$S_i\, w(i)x(i), \leq t$ [3]

All x(i) are greater than 0 and integer

Decision Variable:

x(i) = number of layers of product i

Constants:

w(i) = weight per layer for SKU i (pounds/layer)

c(i) = total weight of SKU corresponding to run-out calculated in step 5 (pounds)

t =total weight of order (pounds)

An Example from Welch's CRP System

Step 1 – Assuming a SKU has dropped below its re-order point, we move to step 2

Step 2 – Table 1 shows beginning inventory netted against forecast

Step 3 – Table 2 converts case forecast (Table 1) into weight per SKU, per day

Step 4 – At the bottom of Table 2, we sum the weight per day for all products

Step 5 – As the cumulative weight per day approaches 44,500 pounds we stop. In the example this occurs at day 12. At this stage, all products have an equal run out, but we are just shy of filling the truck (at day 12, cumulative weight equals 38,793 pounds, at day 13 the cumulative weight is 49,534). We also do not have each product rounded to even case layers.

Step 6 – The total weight for each SKU found in step 5 becomes c(i), the right hand side of equation 2. By solving the IP, we find the number of layers for each item that results in a truck weight as close to 44,500 pounds as possible. Equation 2 ensures a near equal run-outs for all items.

We used What's Best (distributed by LINDO systems) to solve the IP. The solution equals 44,483 pounds. Calculation time equaled a few seconds on a 486, 66 MHz computer.

Typically, the CRP software used at Welch's builds orders within 300 to 500 pounds of maximum order weight. It appears the truck loading procedure outlined above reduces air weight significantly compared to our current software.

We add a word of caution concerning IP. Heavily constrained problems may take a great deal of time to solve. In our opinion, there is little risk of long runs times with the procedure as outlined. We believe this is so because of the structure of the formulation. If a nonfeasible situation does arise, we suggest backing off one or two days in step 5.

Table 1—Forecast Netted for Inventory (all values in cases)

	Days												
Product Code	1	2	3	4	5	6	7	8	9	10	11	12	13
4180021100	0	0	0	0	0	0	0	0	0	0	15	15	15
4180022800	0	0	0	0	7	7	7	6	6	6	6	6	6
4180022900	0	0	0	0	0	0	0	0	0	0	0	18	18
4180050200	0	0	0	0	0	0	0	0	0	0	0	0	5
4180050300	0	0	0	0	0	0	0	7	7	7	7	7	7
4180050500	0	0	0	0	0	0	0	0	0	0	0	6	6
4180050701	0	0	0	0	0	0	0	0	0	0	3	3	3
4180055200	0	0	0	0	0	0	0	0	0	0	0	14	14
4180055300	0	0	0	0	0	0	0	0	0	0	0	3	3
4180056300	0	0	0	0	0	0	0	0	0	0	0	4	4
4180070500	0	0	0	0	0	0	0	0	0	0	0	14	14
4180010300	0	0	0	0	0	0	21	20	20	20	20	20	20
4180010900	0	0	0	0	0	0	0	0	32	32	32	32	32
4180011500	0	0	0	0	0	0	60	54	54	54	54	54	54
4180011600	0	0	0	0	0	0	0	40	40	40	40	40	40
4180011700	0	0	0	0	0	0	0	52	52	52	52	52	52
4180011900	0	0	0	0	0	0	0	0	65	65	65	65	65
4180012800	0	0	0	0	0	0	0	0	17	17	17	17	17
4180013300	0	0	0	0	0	0	0	0	0	0	54	54	54
4180013500	0	0	0	0	0	0	0	0	0	61	61	61	61
4180013600	0	0	0	0	0	0	0	0	52	52	52	52	52
4180014000	0	0	0	0	0	0	0	47	47	47	47	47	47
4180014500	0	0	0	0	0	0	0	0	20	20	20	20	20
4180015000	0	0	0	0	0	0	0	0	19	19	19	19	19
4180015100	0	0	0	0	0	0	0	0	0	0	0	9	9
4180018100	0	0	0	0	0	0	0	15	15	15	15	15	15
4180018200	0	0	0	0	0	0	0	17	17	17	17	17	17

Upon producing a customer order, the CRP system holds order quantities in an "in-transit" classification until the customer receives the shipment. This becomes important as we begin to discuss the role of production planning at plants.

FINITE PRODUCTION PLANNING AND SCHEDULING

The output of the CRP system becomes the forecast for production planning and scheduling at plants. The success of CRP systems rests on the ability of plant based planning and scheduling systems to provide a high level of stock availability. This means planning and scheduling systems must handle limitations on production capacity. The quickest road to failure in CRP is to plan customer shipments and find no inventory exists to cover shipments as scheduled.

Schuster and Allen [1995] highlight the opinion that traditional MRP II may not work well in a CRP environment. Closed loop planning, characteristic of MRP II, might prove too slow to deal with rapid exchange of information between trading partners. This raises questions concerning what types of systems will replace MRP II.

It is a safe bet that finite planning (FP) systems will become the base on which to build CRP systems. There are many different types of FP systems available today. In general, these systems use either heuristic, simulation or optimal based solution methods. We find no single solution method provides the best results. Rather, a mixture of models leads to the best fit for particular situations. Several articles provide a guide for designing FP systems for consumer goods firms [see Allen and Schuster, 1994; Gascon, Leachman and DeGuia, 1993]. We make no claim this direction is the only path to take. Heuristics and non linear programming also offer areas of great potential in FP [see Allen, 1995; Allen 1990].

Given FP systems can yield capacity feasible schedules, CRP should work smoothly for most consumer goods manufacturers. However, if raw materials are not available as planned, FP will fail to produce acceptable results for CRP. Material requirements planning MRP must work in concert with FP.

MATERIAL REQUIREMENTS PLANNING

With capacity feasible production plans, MRP calculates lot sizing and timing of raw materials purchases. Vendors use this information to plan their production. For many years, people outside the process industries considered MRP for consumer goods firms a trivial case. Flat bills of material and short lead times made the problem of material planning look easy compared with discrete manufacturing. However, many overlooked the large volumes of raw material flowing from vendors to manufacturing firms. Any interruption in the flow of raw materials proves disastrous to consumer goods firms.

Most vendors carry substantial buffer inventories to guarantee manufacturers will not run out of raw materials. Many vendors have capital intensive plants that impose constraints on scheduling of production. Buffer inventory provides a

Table 2—Accumulated Weight per Day (all values in pounds)

Product Code	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Cumulated Weight Per Product (12 Days)
4180021100	0	0	0	0	0	0	0	0	0	0	593	593	593	1185
4180022800	0	0	0	0	330	330	330	243	243	243	243	243	243	2204
4180022900	0	0	0	0	0	0	0	0	0	0	0	708	708	708
4180050200	0	0	0	0	0	0	0	0	0	0	0	0	157	0
4180050300	0	0	0	0	0	0	0	88	88	88	88	88	88	442
4180050500	0	0	0	0	0	0	0	0	0	0	0	128	128	128
4180050701	0	0	0	0	0	0	0	0	0	0	61	61	61	121
4180055200	0	0	0	0	0	0	0	0	0	0	0	468	468	468
4180055300	0	0	0	0	0	0	0	0	0	0	0	42	42	42
4180056300	0	0	0	0	0	0	0	0	0	0	0	46	46	46
4180070500	0	0	0	0	0	0	0	0	0	0	0	531	531	531
4180010300	0	0	0	0	0	0	526	489	489	489	489	489	489	2970
4180010900	0	0	0	0	0	0	0	0	417	417	417	417	417	1666
4180011500	0	0	0	0	0	0.	751	675	675	675	675	675	675	4124
4180011600	0	0	0	0	0	0	0	521	521	521	521	521	521	2603
4180011700	0	0	0	0	0	0	0	650	650	650	650	650	650	3251
4180011900	0	0	0	0	0	0	0	0	817	817	817	817	817	3270
4180012800	0	0	0	0	0	0	0	0	215	215	215	215	215	861
4180013300	0	0	0	0	0	0	0	0	0	0	676	676	676	1352
4180013500	0	0	0	0	0	0	0	0	0	757	757	757	757	2271
4180013600	0	0	0	0	0	0	0	0	645	645	645	645	645	2582
4180014000	0	0	0	0	0	0	0	585	585	585	585	585	585	2925
4180014500	0	0	0	0	0	0	0	0	503	503	503	503	503	2013
4180015000	0	0	0	0	0	0	0	0	208	208	208	208	208	832
4180015100	0	0	0	0	0	0	0	0	0	0	0	99	99	99
4180018100	0	0	0	0	0	0	0	198	198	198	198	198	198	988
4180018200	0	0	0	0	0	0	0	222	222	222	222	222	222	1112
Total Wt./Day	0	0	0	0	330	330	1607	3670	6476	7233	8562	10584	10741	38793
Cumulated 0	0	0	0	330	660	2267	5937	12413	19647	28209	38793	49534		

quick solution to overcome constraints. Nonetheless, with increasing competitiveness and greater threat of obsolescence, vendors find it difficult to justify increased inventory.

To combat this problem, a new breed of MRP is close to commercial application. Combining attributes of linear programming and MRP, the new systems handle constrained material planning problems [see Leachman, 1993; Leachman, 1996]. This offers the prospect of consumer goods firms planning raw materials purchases based on capacity constraints at vendors. If this happens, it will eliminate one more source of deviation in the supply chain.

NEW DIRECTIONS IN SUPPLY CHAIN MANAGEMENT

There remains a great deal of work to fully integrate supply chains. In the process of building EDI connections within the supply chain, entire new business opportunities will emerge. It is hard to predict how new business will unfold. Several authors offer interesting insights [Bessen, 1993; Grant and Schlesinger, 1995; Rayport and Sviokla, 1994; Tapscott, 1995, p. 63]. We discuss two of the more promising prospects.

Data Envelopment Analysis

A relatively new way of looking at performance, data envelopment analysis (DEA), has its foundation in Charnes, Cooper and Rhodes [1978]. Since publication of this article, an explosion of research on DEA occurred. Seiford [1990] organizes research on DEA into a bibliography used widely in academia. To date, most applications of DEA take place in public sector settings. It is only recently that researchers turned attention to business problems.

DEA is an application of linear programming that measures the relative efficiency of decision making units (DMU) with the same goals and objectives [Anderson, Sweeney and Williams (1994), p.192]. Essentially, DEA is a sophisticated way to do benchmarking between DMU's. A DMU is any system that has measurable inputs and outputs. Examples include schools, branch banks, computer systems and investment funds. Several recent articles show interesting applications of DEA in the public sector and business [Adolphson, Cornia and Walters, 1989; Sherman and Ladina, 1995].

With greater information flow through EDI, it becomes possible to build DEA models of the relative performance of trade customers. For example, a consumer goods manufacturer might decide to measure the relative efficiency of different trade customers in turning promotional discounts into sales. Manufacturers are in the best position to see how well different trade customers merchandise their products. Benchmarking of trade customers uncovers best practices. This information has value not only to consumer goods manufacturers, but also to other trade customers.

The data requirements for DEA are massive. It will be several years before DEA reaches widespread use as a tool in SCM. Initial applications of DEA will probably focus on studies comparing relative efficiency of different stores. We know of one consulting firm that already offers this service.

Game Theory

Strategy and competition are terms we hear every day in business. An important role of managers involves formulation of plans to gain advantage in the marketplace. Market share gains do not come without a response from competition. Game theory attempts to analyze how other players react to your moves in the marketplace.

With greater information about the supply chain, consumer goods companies are in an excellent position to take advantage of game theory. Like DEA, game theory is often data intensive. However, some examples exist where application of game theory brought great success [see Brandenburger and Nalebuff, 1995]. For an introduction to game theory, see Hillier and Lieberman [1980].

CONCLUSION

Our view of SCM includes a rigorous approach that relies on building practical mathematical models for planning and control. We see a future filled with potential to eliminate cost from the supply chain. In planning for the future, we must not lose sight of subtle changes in our thinking that are taking place. The current environment of rapid change and uncertainty creates entirely new ways for looking at problems [see Freedman, 1992]. We hope that through this paper, and the accompanying references, you will experiment with some of the new technology available today.

REFERENCES

Adolphson, D.L., G.C. Cornia and L.C. Walters. 1989. "Railroad Property Valuation Using Data Envelopment Analysis." *Interfaces*, Vol. 19, No. 3.

Allen, S.J. 1990. "Production Rate Planning for Two Products Sharing a Single Process Facility: A Real World Case Study." *Production and Inventory Management Journal*, Third Quarter.

Allen, S.J., and E.W. Schuster. 1994. "Practical Production Scheduling With Capacity Constraints And Dynamic Demand: Family Planning and Disaggregation." *Production and Inventory Management Journal*, 4th quarter.

Allen, S.J. 1995. "Short—Term Finite Scheduling Systems: The Key to Establishing Realistic Priorities." *The 1995 Process Industry Technical Conference* (Erie, PA), June.

Anderson, D.R., D.J. Sweeney and T.A. Williams. 1994. *Introduction to Management Science: Quantitative Approaches to Decision Making*. West Publishing (St. Paul, Minnesota).

Andrews, B.H. and S.M. Cunningham. 1995. "L.L. Bean Improves Call—Center Forecasting." *Interfaces*, Vol. 25, No. 6, November –December.

Armstrong, J.S. 1984. "Forecasting by Extrapolation: Conclusions from Twenty-Five Years of Research." *Interfaces*, Vol. 14.

Arntzen, B.C., G.G. Brown, T.P. Harrison and L.L. Trafton. 1995. "Global Supply Chain Management at Digital Equipment Corporation." *Interfaces*, Vol. 25, No.1, January–February.

Bessen, J. 1993. "Riding the Marketing Information Wave." *Harvard Business Review*, September–October.

Bowersox, D.J. 1990. "The Strategic Benefits of Logistics Alliances." *Harvard Business Review*, July–August.

Brandenburger, A.M. and B.J. Nalebuff. 1995. "The Right Game: Use Game Theory to Shape Strategy." *Harvard Business Review*, July–August.

Buzzell, R.D., J.A. Quelch and W.J. Salmon. 1990. "The Costly Bargain of Trade Promotion." *Harvard Business Review*, March–April.

Charnes, A., W.W. Cooper and E. Rhodes. 1978. "Measuring the Efficiency of Decision Making Units." *European Journal of Operations Research*, Vol. 2, No. 6.

Cleaves, G.W. and V.A. Masch. 1996. "Strengthening Weak Links." *OR/MS Today*, published by the Institute for Operations Research and Management Science (INFORMS), April.

Cook, R.L. and R.A. Rogowski. 1996. "Applying JIT Principles to Continuous Process Manufacturing Supply Chains." *Production and Inventory Management Journal*, First Quarter.

Davis, G.B and H.H. Olson. 1985. *Management Information Systems*. McGraw-Hill (New York).

D'Itri, M.P. and E.W. Schuster. 1995. "Continuous Replenishment Systems in the Process Industries: Implementation Issues and Ideas for Productivity Improvements." *The 1995 Process Industry Technical Conference* (Erie, PA), June.

Fisher, M.L., J.H. Hammond, W.R. Obermeyer and A. Raman. 1994. "Making Supply Meet Demand in an Uncertain World." *Harvard Business Review*, May–June.

Fisher, M and A. Raman. 1996. "Reducing the Cost of Demand Uncertainty Through Accurate Response to Early Sales." *Operations Research*, Vol. 44, No. 1. January–February.

Flowers, A.D. 1993. "The Modernization of Merit Brass." *Interfaces*, Vol. 23, No. 1, January-February.

Freedman, D.H. 1992. "Is Management Still a Science?" *Harvard business Review*, November–December.

Fuller, J.B., J. O'Connor and R. Rawlinson. 1993. "Tailored Logistics: The Next Advantage." *Harvard Business Review*, May–June.

Gascon, A., R.C. Leachman and A.A. DeGuia. 1993. "Optimal Planning and Control of Consumer Products Packaging Line." in *Optimization in Industry*. John Wiley & Sons (New York).

Grant, A.W.H. and L.A. Schlesinger. 1995. "Realize Your Customer's Full Profit Potential." *Harvard Business Review*, September–October.

Haeckel, S.H. and R.L. Nolan. 1993. "Managing By Wire." *Harvard Business Review*, September–October.

Hammel, T.R. and L.R. Kopczak. 1993. "Tightening the Supply Chain." *Production and Inventory Management Journal*, 2nd quarter.

Hillier, F.S. and G.J. Lieberman. 1980. *Introduction to Operations Research*. Holden-Day, Inc. (San Francisco).

Leachman, R.C. 1993. "Modeling Techniques for Automated Production Planning in the Semiconductor Industry." in *Optimization in Industry*. John Wiley & Sons (New York).

Leachman, R.C., R.F. Benson, C. Liu and D.J. Raar. 1996. "IMPReSS: An Automated Production-Planning and Delivery-Quotation System at Harris Corporation—Semiconductor Sector." *Interfaces*, Vol. 26, No. 1, January–February.

Lee, H.L. and C. Billington. 1993. "Material Management in Decentralized Supply Chains." *Operations Research*, Vol. 41, No. 5, September–October.

Lee, H.L. and C. Billington. 1995. " The Evolution of Supply-Chain-Management Models and Practice at Hewlett-Packard." *Interfaces*, Vol. 25, No. 5, September–October.

Malone, T.W., J. Yates and R.I. Benjamin. 1989. "The Logic of Electronic Markets." *Harvard Business Review*, May–June.

Martin, A.J. 1983. *Distribution Resource Planning*, Prentice- Hall (Englewood Cliffs, NJ).

Martin, A.J. and D.D. Landvater. 1995. "Customer—Driven Continuous Replenishment Program—The Ultimate ECR Strategy." *38th International Conference Proceedings of APICS (Orlando)*, October.

Nahmias, S. 1993. *Production and Operations Analysis*. Irwin (Boston, MA).

Pankratz, A. 1983. *Forecasting With Univariate Box-Jenkins Models*. John Wiley & Sons (New York).

Park, S. 1994. "Quick Response with Overseas Production." *Production and Inventory Management Journal*, 4th quarter.

Perry, D. and D. Ross. 1995. "Imagineering the Future of Continuous Replenishment in the Food Industry: A Canadian Perspective." *38th International Conference Proceedings of APICS (Orlando)*, October.

Pine, B.J., B. Victor and A.C. Boynton. 1993. "Making Mass Customization Work." *Harvard Business Review*, September–October.

Pooley, J. 1994. "Integrated Production and Distribution Facility Planning at Ault Foods." *Interfaces*, Vol. 24, No. 4, July–August.

Porter, M.E. 1985. *Competitive Advantage*. Free Press - Macmillan (New York).

Rayport, J.F. and J.J. Sviokla. 1994. "Managing in the Marketspace." *Harvard Business Review*, November–December.

Rayport, J.F. and J.J. Sviokla. 1995. "Exploiting the Virtual Value Chain." *Harvard Business Review*, November–December.

Robinson, E.P., L. Gao and S.D. Muggenborg. 1993. "Designing an Integrated Distribution System at DowBrands, Inc." *Interfaces*, Vol. 23, No. 3 May–June.

Ross, D.F. 1995. "Designing an Effective Quick Response System." *38th International Conference Proceedings of APICS (Orlando)*, October.

Schuster, E.W., and B.J. Finch. 1990. "A Deterministic Spreadsheet Simulation Model for Production Scheduling in a Lumpy Demand Environment." *Production and Inventory Management Journal*, 2nd quarter.

Schuster, E.W. and S.J. Allen. 1995. "A New Framework for Production Planning in the Process Industries." *38th International Conference Proceedings of APICS (Orlando)*, October.

Sharda, R. 1994. "Neural Networks for the MS/OR Analyst: An Application Bibliography." *Interfaces*, Vol. 24, No. 2, March–April.

Sherman, H.D. and G. Ladina. 1995. "Managing Bank Productivity Using Data Envelopment Analysis." *Interfaces*, Vol. 25, No. 2, March–April.

Shapiro, J.F., V.M. Singhal and S.N. Wagner. 1993. "Optimizing the Value Chain." *Interfaces*, Vol. 23, No. 2, March–April.

Seiford, L.M. 1990. "A Bibliography of Data Envelopment Analysis (1987–1990)." Published by the Dept. of Industrial Engineering and Operations Research, University of Massachusetts Amherst.

Stalk G., Evans, P. and L.E. Shulman. 1992. "Competing on Capabilities: The New Rules of Corporate Strategy." *Harvard Business Review*. March–April.

Sterman, J.D. 1992. "Teaching Takes Off: Flight Simulators for Management Education." *OR/MS Today*, published by the Institute for Operations Research and Management Science (INFORMS), October.

Tapscott, D. 1995. *The Digital Economy*. McGraw-Hill (New York).

Taube-Netto, M. 1996. "Integrated Planning for Poultry Production at Sadia." *Interfaces*, Vol. 26, No. 1, January - February.

ABOUT THE AUTHORS

Edmund W. Schuster, CPIM, CIRM, is manager of logistics planning at the corporate office of Welch's located in Concord, MA. He has a B.S. in Food Technology from The Ohio State University and an M.P.A. from Gannon University (Erie, PA). An active member of APICS, Ed is past president of the Erie, PA, chapter and past chair of the APICS Process Industry Group. He is currently the associate director of the Center for Process Manufacturing at Penn State Erie.

Michael P. D'Itri, Ph.D., is an Assistant Professor of Management Science and Information Systems at Penn State Erie, The Behrend College. He is also a research associate at the Center for Process Manufacturing. He has earned three degrees from Michigan State University: a B.S. degree in Chemical Engineering, an M.B.A. in Management Science and a Ph.D. in Operations Management. Mike's primary research interests are in the area of production scheduling, with particular emphasis on the manufacture of paper. He has also done work on exchange rate risk management and other types of math modeling. He has co-authored articles that have appeared in the *International Journal of Physical Distribution and Logistics Management* and the *International Journal of Purchasing and Materials Management*.

Stuart J. Allen, Ph.D., is an associate professor of management at Penn State Erie. Stuart received a Ph.D. in engineering mechanics from the University of Minnesota. He is interested in the application of management science tools in actual production settings and his work has appeared in P&IM. He is a member of the Center for Process Manufacturing at Penn State Erie and currently serves on the APICS Process Industry SIG Steering Committee. Besides his academic career, Stuart has owned several small businesses.