Proceedings of the 2006 Winter Simulation Conference
L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol, and R. M. Fujimoto, eds.

USING SYSTEM DYNAMICS SIMULATIONS TO COMPARE CAPACITY MODELS FOR PRODUCTION PLANNING

Seza Orcun

Laboratory for Extended Enterprises
at Purdue
e-Enterprise Center at Discovery Park
Purdue University
Burton D. Morgan Building
1201 West State Street
West Lafayette, IN 47907-2057, U.S.A.

Reha Uzsoy

Laboratory for Extended Enterprises
at Purdue
School of Industrial Engineering
Purdue University
Grissom Hall
315 N. Grant Street
West Lafayette, IN 47907-2023, U.S.A.

Karl Kempf

Director, Decision Technologies
Intel Corporation
5000 W. Chandler Blvd., MS
CH3-10
Chandler, AZ 85226, U.S.A.

ABSTRACT

While a variety of optimization formulations of production planning problems have been proposed over the last fifty years, the majority of these are based on simple models of capacity that fail to reflect the nonlinear relationship between workload and lead times induced by the queuing behavior of capacitated production resources. We use system dynamics simulations of a simple capacitated production system to examine the performance of several different capacity models that yield load-dependent lead times, and relate these models to those used in system dynamics models of production systems.

1 INTRODUCTION

The production planning problem may be defined as that of assigning available production resources to different products over time to optimize some measure of the firm's performance. The formulation of these problems as deterministic optimization problems dates back to the seminal work of (Modigliani and Hohn 1955) and (Holt et al. 1956). The basic approach of most of these models, whether they be integer or linear programs, is to divide the time horizon over which production is to be planned into discrete time periods. Within each period the capacity of each production resource is represented in some aggregate manner, usually as the total number of hours the resource can be loaded during the time bucket. Decision variables are associated with each planning period representing, at a minimum, the planned production or release quantities and ending inventories of each product for that period. However, in order to effectively match the firm's production to its demand, production planning models need to consider the lead times that elapse between work being released into the plant and its emergence as finished product that can be used to meet demand. The vast majority of existing linear and integer programming models for production planning (Hackman and Leachman 1989; Johnson and Montgomery 1974), as well as the widely used Material Requirements Planning (MRP) procedure (Orlicky 1975), treat lead times as exogeneous parameters independent of the decision variables in the model. This leads to a fundamental circularity in these kinds of models. Queuing models (Hopp and Spearman 2001; Buzacott and Shanthikumar 1993) tell us that lead times increase nonlinearly in both mean and variance with resource utilization. However, the work release decisions made by the planning model determine the utilization level of the production resources in a planning period, and hence the lead times that will be realized.

In recent years there has been growing interest in developing production planning models using representations of capacity that permit the representation of workload-dependent lead times (Pahl et al. 2005). In this paper we use system dynamics simulations (Sterman 2000) of a simple capacitated production system to examine the behavior of several different capacity models that have been suggested in the production planning context. We also relate several of these models to counterparts in the system dynamics literature as well as some approaches suggested in the system dynamics literature for modeling the behavior of production resources.

In the following section we give a brief review of previous work related to modeling production systems with load-dependent lead times. We then focus on a particular class of these models, those based on clearing functions that represent the relationship between the expected output of the production system in a planning period and the expected work in process inventory (WIP) level during that period. Section 4 presents the design of the simulation experiments, together with the implementation of these models in the VENSIM software. We then present the results of the simulation experiments and discuss their significance. The paper concludes with a summary of the principal insights and some directions for future research.

2 PREVIOUS RELATED WORK

While a variety of definitions of manufacturing capacity are discussed in both the academic and the trade literature, accurate measurement of manufacturing capacity is surprisingly difficult (Elmaghraby 1991). The amount and mix of output a capacitated production resource can produce over a specific time interval can depend on lot sizes, processing times, the distributions of the random variables associated with the system, the mix of products to be produced. An extensive literature has been developed using stochastic models, particularly queuing models, to examine the effects of these different factors on the performance of production systems (Buzacott and Shanthikumar 1993; Karmarkar 1993; Hopp and Spearman 2001). In particular, queuing research has shown that lead times increase nonlinearly with resource utilization in both expectation and variance, and that this degradation of lead times begins to be observed long before the utilization reaches to 1. Thus, deterministic production planning models that seek to effectively match the firm's supply to its estimated demand over time are faced with a circularity: in order to match supply to demand, the model must capture lead times, but lead times are a result of the planning decisions made by the model itself.

There have been two basic approaches to this problem in the literature. By far the most common is to treat lead times as an exogeneous parameter independent of the decision variables in the planning model. A thorough discussion of this approach is given by (Hackman and Leachman 1989). The other approach is to link the planning model to a detailed scheduling or simulation model that determines whether the plans developed by the planning model are actually feasible. Examples of this type of approach are given by Pritsker and Snyder (1997) and Dauzere-Peres and Lasserre (1994).

A number of authors have proposed enhanced LP formulations that model the dependency between lead times and resource utilization to some degree. Lautenschlager and Stadtler (1998) suggest a model where the lead times are captured by allowing the production in a given period to become available over several future periods. Voss and Woodruff (2003) propose a nonlinear model where the function linking lead time to workload is approximated as a piecewise linear function. Other authors, such as Kekre (1984) and Ettl et al. (2000) have followed a similar approach, essentially including a nonlinear term representing the costs of carrying WIP as a function of workload in the objective function. The clearing function (CF) approach differs in that the nonlinear behavior of the system is embedded in the constraints rather than the objective function.

Other authors have suggested iterative techniques for addressing the fundamental circularity. Riano et al. (2003) present a formulation that models random lead times, but assumes that lead time distributions for products are independent, which is unlikely if they share production capacity. In addition, the distribution of lead times appears to be time-stationary, which is again of limited accuracy if workloads vary over time. In subsequent work Riano (2003) derived an iterative approach based on estimating the fraction of the work released in a given period that will emerge as output in a given future period. An initial set of release decisions is made and the weights associated with that release pattern are estimated. A linear programming model using these weights is then solved to obtain a new release pattern, and the iteration proceeds until convergence. Hung and Leachman (1996) propose an alternative iteration scheme where an initial set of lead time estimates is obtained and used in an LP model that determines work release decisions over time. The resulting releases are then simulated to estimate the realized lead times associated with that release pattern, and the realized lead times are now used for another iteration of the planning model. This approach is further refined in (Hung and Hou 2001).

A promising approach to capturing the relationship between workload and lead times in production planning that has received increasing interest recently (Pahl et al. 2005) is the use of clearing functions, originally suggested by Graves (1986, 1988) and further developed by Karmarkar (1989) and Srinivasan et al. (1988). These approaches form the focus of the simulation models in this paper, and are described in the following section.

System dynamics models (Sterman 2000; Forrester 1962) have been used extensively for decades to model supply chains. As such, they include their own representations of manufacturing capacity and the relationship between workload, WIP and lead times. In this paper we use system dynamics models to examine the behavior of different models of manufacturing capacity in the face of different demand patterns. Our objectives are to illustrate the assumptions about system behavior that are implicit in the different capacity models, and to link the system dynamics terminology to that used in the production planning community in order to facilitate interaction between these areas in the future.

3 CLEARING FUNCTIONS

As suggested by Graves (1986, 1988), a clearing function relates the expected output of a production resource over a given planning period to the WIP level during that period. Figure 1 illustrates several different clearing functions studied in the literature along with other models of the relationship between WIP and throughput. The "Constant Proportion Clearing Function (CPCF)" of (Graves 1986) allows unlimited output in a planning period, but ensures fixed lead-time. However, by linking production rate to WIP level, it differs from the fixed delays used in most LP models, where the output of a production process is simply the input shifted forward in time by the fixed lead time. The "Fixed Capacity" function corresponds to a fixed upper bound on output over the period, but without a lead-time constraint it implies instantaneous production, since production occurs without any WIP in the system. This is reflected in the independence of output from the WIP level, which may constrain throughput to a level below the upper bound by starving the resource. Typical LP formulations enforce an upper bound on output via an aggregate capacity constraint and allow the possibility of output being constrained by available inventory levels through the presence of inventory balance constraints. This latter is denoted by the "Fixed Exogenous Lead Time (FELT)" line, whose slope is equal to the inverse of the unit average processing time of work at the resource. This approach is implemented in, for example, the MRP-C approach of (Tardif and Spearman 1997) and the LP approaches of (Hackman and Leachman 1989) and (Billington et al. 1983). It is apparent from the figure that the clearing function always lies below the "FELT" and "Fixed Capacity" lines, which together represent the capacity constraints of a typical LP model.

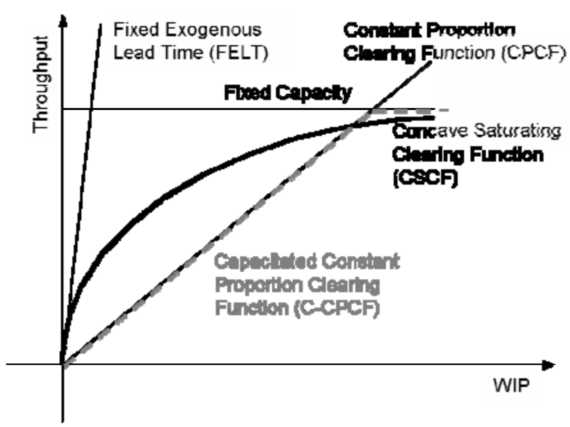

Figure 1: Different Clearing Functions

Karmarkar (1989) and Srinivasan et al. (1988) propose production planning formulations using clearing functions for single product systems. Asmundsson et al. (2006) and Asmundsson et al. (2006) extend these formulations to multiple product systems, discuss the estimation of the clearing functions form empirical data and provide extensive computational experiments comparing the performance of the clearing function models to that of conventional linear programming models with fixed lead times. Our objective in this paper is to compare the behavior of this representation of production capacity relative to other commonly used representations in production planning and system dynamics.

4 CAPACITY MODELS SIMULATED

In this section we describe the different models of capacity that constitute the simulation models used. For simplicity of exposition we shall focus on a single product production system consisting of a number of machines or machine groups. We shall denote the amount of work released to the system at the beginning of period t by R_t, the output of the production system over that period by X_t and the amount of WIP in the system at the end of the period by W_t. The amount of inventory of finished product at the end of period t is denoted by I_t, and the exogenous demand for the product during the planning period by D_t. Our primary focus will be on the relationship between R_t, W_t and X_t. Finally, we shall denote the maximum possible output of the system in period t by C_t. In practice this would represent the production rate of the bottleneck resource. All quantities are defined in units of time; thus, for example, R_t represents the number of hours of work released into the system in period t. We now describe the different capacity models simulated.

4.1 Fixed Exogenous Lead Time

This representation of lead times, which we will refer as FELT, is common both in the mathematical programming literature on production planning and the inventory literature. The lead time of the production system is represented as a fixed, exogenous constant L. Thus the behavior of this system is characterized by the relationship

$$X_t = R_{t-L} \quad (1)$$

In systems dynamics terminology, this is a pipeline or fixed delay (Sterman 2000, p. 411) where the output of the process emerges from the process in exactly the order in which it enters, but L time units after it entered with perfect conservation of material.

4.2 Constant Proportion Clearing Function

This clearing function, which we shall denote by CPCF, was first proposed and analyzed by Graves (1986, 1988) based on empirical observation of a manufacturing plant described in (Fine and Graves 1989). The governing relationship here is given by

$$X_t = \frac{W_t}{L} \quad (2)$$

where L is the lead time (in time units). For example, if the lead time is 4 time units then this model states that in a given time unit only 25% of the work-in-progress is processed to completion.

In system dynamics terminology, this is a first-order material delay (Sterman 2000, p. 416), which assumes perfect mixing of the units in the WIP; essentially any item in WIP has the same probability of emerging as output regardless of when it entered the system.

4.3 Capacitated Constant Proportion Clearing Function

An obvious disadvantage of the CPCF is apparent from Figure 1: at high WIP levels it will suggest output levels in excess of the available resource capacity C_t. The Capacitated CPCF model, denoted by C-CPCF (depicted with dashed line in Figure 1), addresses this by limiting the maximum output in a period, giving

$$X_t = \min \{ \frac{W_t}{L}, C_t \}. \tag{3}$$

4.4 Concave Saturating Clearing Function

This is the form of clearing function suggested by Karmarkar (1989) and Srinivasan et al. (1988). We shall denote it by CSCF in the remainder of the paper. The intuition is that as the utilization increases, the congestion effects of queuing cause the output to increase with WIP but at a decreasing rate. Extensive empirical analysis using simulation models supports the assumption that this function will be concave; Asmundsson et al. (2006) show that clearing functions derived from steady-state queuing relationships such as the Pollaczek-Khintchine formula for the *M/G/1* queue or from queuing analysis of the short-term behavior of the queue yield functions with the postulated concave form. In our experiments we use a CSCF of the form

$$X_t = \frac{C_t W_t}{W_t + K}, \tag{4}$$

where K is a user-defined parameter controlling the curvature of the function. Note that this functional form yields

$$\lim_{W_t \to \infty} X_t = C_t. \tag{5}$$

In system dynamics terminology, this type of function is called a *Fuzzy MIN* function discussed by (Sterman 2000, p. 529). Interestingly, he does not use this function in the models of capacitated manufacturing systems he develops in later chapters.

The majority of the researchers in the production community who work with clearing functions derive them from some form of queuing model. It is interesting to note that essentially the same model can be derived using a system dynamics approach, which we present in the following section.

5 SIMULATION EXPERIMENTS

The purpose of the simulation experiments presented in this section is to examine behavior of an arbitrary production facility modeled at aggregate level using the different approaches presented in the previous section. Thus, this section provides insights independent of any given industry for discrete manufacturing systems within planning context. While the specific nature of the flows within the production system may be quite complex, such as reentrant flows encountered in semiconductor manufacturing (Uzsoy et al. 1992), we represent the production system using simple input-output relationships typical of those used in optimization formulations of production planning problems. Asmundsson et al. (2006) give an extensive discussion of the estimation of clearing functions in reentrant flow systems. The simulations were developed using the VENSIM simulation software by Ventana Systems. Figure 2 depicts the causal diagram of the C-CPCF model. As discussed in (Sterman 2000), together with the equations defining the flows (Starts and Production Rate), these constitute a complete description of the system dynamics models used. The releases to the production facility are represented by the *Starts* flow which simulates a pulse release of 100 units starting at week 50 for 100 weeks (see last plot in Figure 3). The work-in-progress is represented by a stock (*WIP*). The output of the production system is modeled by another flow whose rate is given by (3). To simulate the other capacity models used, the flow expression is modified to the appropriate expression given in the previous section. Finished products are accumulated in the *Inventory* stock.

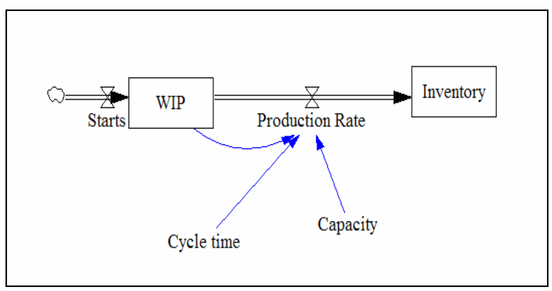

Figure 2: Causal Diagram of C-CPCF model

The diagrams for the other simulations are similar and can be obtained from the authors on request. In all simulations, we used the parameter settings given in Table 1 to facilitate fair comparison of models. The relationship between these parameters will be highlighted as the associated simulations results are being discussed. We simulate the behavior of each capacity model presented in the previous section using two different pulse inputs, one at low utilization

(0.33) and one at high utilization (1.033). The latter scenario represents a situation where the input temporarily exceeds the capacity of the resource, and permits us to show the effect of the different capacity models when significant congestion effects are present.

Table 1: Simulation Parameters

Simulation Horizon	200 weeks
Integration Time Step	1 week
Capacity	300
Curvature (K)	800
Average Cycle Time	4 weeks
Raw Processing Time	8/3 weeks
Low Utilization Run Pulse	100
Congestion Run Pulse	310

Figure 3 shows the simulation results for low utilization runs for FELT, CPCF, C-CPCF, CSCF, First Order Delay and Third Order Delay models. FELT model responds to the pulse release with a fixed 4 weeks delay which is the perfect pipeline. CPCF and First Order Delay (with average cycle time) exactly coincides on top of each other as expected theoretically. Notice that the system takes longer than the average cycle time to adapt to the disruption. C-CPCF is also coincides with CPCF and First Order Delay due to the low utilization (33.33%). The third order delay with average cycle time response approaches the pipeline response since, as discussed by (Sterman 2000), as the order of delay increases the system adapts to the disturbances more rapidly and the pipeline delay is an infinite-order delay. The CSCF model responds to the change in the release impulse slowest but close to CPCF. This lag is due to the fact that actual (observed) capacity reaches the theoretical capacity C_t asymptotically in the CSCF model. This effect becomes more apparent when the system is running at higher utilization as seen in Figure 4.

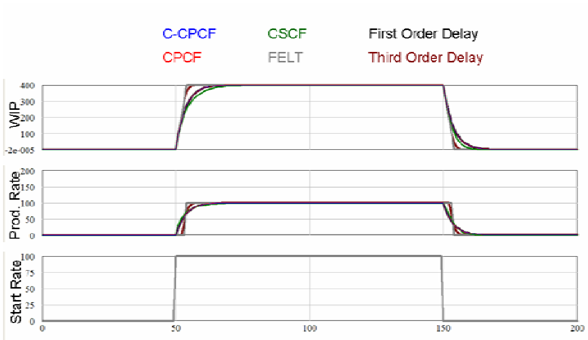

Figure 3: Comparison of Models: Low Utilization

In Figure 4, all models except for CSCF respond to the pulse release of magnitude 310, which is higher than the theoretical capacity $C_t = 300$, in an almost identical manner to the low utilization case. This suggests that they fail to capture the congestion phenomena observed in many manufacturing setups. The curvature K of the clearing function was calculated to be 800 based on an assumed raw processing time, i.e., throughput time of the line with no congestion, of 2.67 weeks.

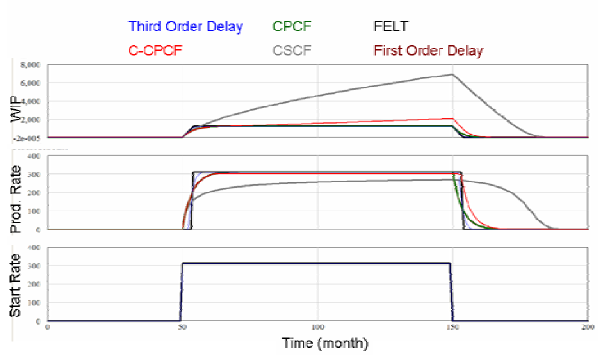

Figure 4: Comparisons of Models: High Utilization

The model presented in Figure 5 shows how a conventional systems dynamics approach might model the behavior of a production system subject to congestion. When the production facility is empty it takes raw processing time to produce the first product. As the WIP accumulates congestion effects begin and hence the cycle time increases. The production rate (throughput) increases at a decreasing rate as WIP accumulates. The model of Figure 5 captures this dependency with a linear relationship between cycle time, WIP, total capacity and raw processing time: cycle time is equal to raw processing time plus WIP divided by total capacity. Note that this linear relationship is identical to the tangent to clearing function given by (4) where the raw processing time is equal to K/C_t. Figure 6 compares this model to CSCF under high utilization condition. As suspected the responses of these two models exactly overlap on to each other.

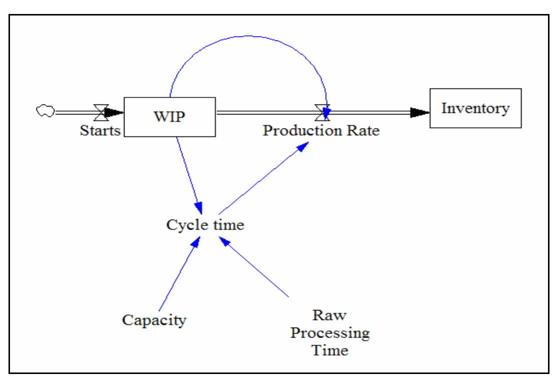

Figure 5: Conventional Systems Dynamics Model

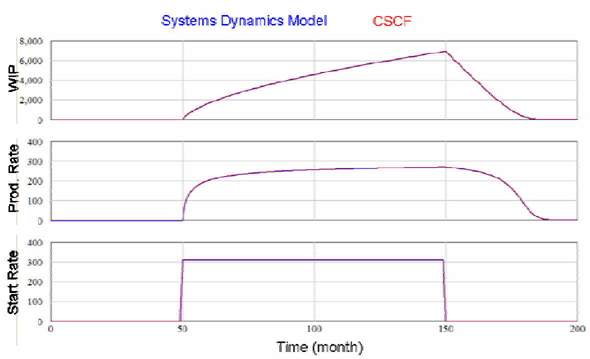

Figure 6: Comparison of Clearing Function to Conventional Systems Dynamics Model

6 CONCLUSIONS

The simple system dynamics simulations presented above show that a number of models used in the production planning and system dynamics literatures fail to capture the behavior of production systems at high utilization. Although all models behave quite similarly at low utilization levels. The CSCF model is shown to represent the nonlinear changes in system performance at high utilization in a manner consistent with insights from queuing models and industrial practice. We have also related the production planning models to those used in the system dynamics community, and shown how to derive the CSCF model using a system dynamics approach rather than the queuing approach from which most clearing functions are derived in the production planning literature. These results imply that the FELT model in widespread use in optimization formulations of production planning problems fails to represent the behavior of production systems at the high utilization levels common in capital-intensive industries such as the semiconductor industry (Atherton, R. W. and J. E. Dayhoff 1986a,b). A natural extension to this work is a comparative study of the effects of policies devised by utilizing these models in production planning optimizations.

ACKNOWLEDGMENTS

Part of this work was done while the second author was a visiting researcher with the Decision Technologies group at Intel Corporation, supported by the Intel Research Council and Purdue University.

REFERENCES

Asmundsson, J. M., R. L. Rardin, C. H. Turkseven, and R. Uzsoy (2006). "Tractable Nonlinear Capacity Models for Production Planning." *Research Report, Laboratory for Extended Enterprises, Purdue University*.

Asmundsson, J. M., R. L. Rardin, and R. Uzsoy (2006). "Tractable Nonlinear Production Planning Models for Semiconductor Wafer Fabrication Facilities." *IEEE Trans. on Semiconductor Mfg.* 19: 95-111.

Atherton, R. W. and J. E. Dayhoff (1986a) “Signature analysis: Simulation of inventory, cycle time, and throughput trade-offs in wafer fabrication,” *IEEE Trans. on Components, Hybrids, and Manuf. Tech.*, vol. CHMT-9, no. 4, pp. 498–507.

Atherton, R. W. and J. E. Dayhoff (1986b). “Signature analysis of dispatch schemes in wafer fabrication,” *IEEE Trans. on Components, Hybrids, and Manuf. Tech.*, vol. CHMT-9, no. 4, pp.518–525.

Billington, P. J., J. O. McClain, and L. J. Thomas (1983). "Mathematical Approaches to Capacity-Constrained MRP Systems: Review, Formulation and Problem Reduction." Management Science 29(10): 1126-1141.

Buzacott, J. A. and J. G. Shanthikumar (1993). *Stochastic Models of Manufacturing Systems*. Englewood Cliffs, NJ, Prentice-Hall.

Dauzere-Peres, S. and J. B. Lasserre (1994). *An Integrated Approach in Production Planning and Scheduling*. Berlin, Springer-Verlag.

Elmaghraby, S. E. (1991). "Manufacturing Capacity and its Measurement: A Critical Evaluation." *Computers and Operations Research* 18(17): 615-627.

Ettl, M., G. Feigin, G. Y. Lin, and D. D. Yao (2000). "A Supply Chain Network Model with Base-Stock Control and Service Requirements." *Operations Research* 48: 216-232.

Fine, C. H. and S. C. Graves (1989). "A Tactical Planning Model for Manufacturing Subcomponents of Mainframe Computers." *Journal of Manufacturing and Operations Management* 2: 4-34.

Forrester, J. W. (1962). *Industrial Dynamics*, MIT Press.

Graves, S. C. (1986). "A Tactical Planning Model for a Job Shop." *Operations Research* 34: 552-533.

Graves, S. C. (1988). "Safety Stocks in Manufacturing Systems." *Journal of Manufacturing and Operations Management* 1: 67-101.

Hackman, S. T. and R. C. Leachman (1989). "A General Framework for Modeling Production." *Management Science* 35: 478-495.

Holt, C. C., F. Modigliani, and J. F. Muth (1956). "Derivation of a Linear Rule for Production and Employment." *Mgmt. Science* 2(2): 159-177.

Hopp, W. and M. L. Spearman (2001). *Factory Physics*, Irwin.

Hung, Y. F. and M. C. Hou (2001). "A Production Planning Approach based on Iterations of Linear Programming Optimization and Flow Time Prediction." *Journal of the Chinese Institute of Industrial Engineers* 18(3): 55-67.

Hung, Y. F. and R. C. Leachman (1996). "A Production Planning Methodology for Semiconductor Manufacturing Based on Iterative Simulation and Linear Programming Calculations." *IEEE Transactions on Semiconductor Manufacturing* 9(2): 257-269.

Johnson, L. A. and D. C. Montgomery (1974). *Operations Research in Production Planning, Scheduling and Inventory Control*. New York, John Wiley.

Karmarkar, U. S. (1989). "Capacity Loading and Release Planning with Work-in-Progress (WIP) and Lead-times." *Journal of Manufacturing and Operations Management* 2(105-123).

Karmarkar, U. S. (1993). Manufacturing Lead-times, Order Release and Capacity Loading. *Handbooks in Operations Research & Management Science Vol. 4: Logistics of Production and Inventory*. S. C. Graves, A. H. G. Rinnooy Kan and P. H. Zipkin.

Kekre, S. (1984). Some Issues in Job Shop Design. Simon Graduate School of Business Administration. Rochester, NY, University of Rochester.

Lautenschlager, M. and H. Stadtler (1998). Modelling Lead Times Depending on Capacity Utilization. Research Report, Technische Univ. Darmstadt.

Modigliani, F. and F. E. Hohn (1955). "Production Planning Over Time and the Nature of the Expectation and Planning Horizon." *Econometrica* 23: 46-66.

Orlicky, J. (1975). *Material Requirements Planning*. New York, McGraw-Hill.

Pahl, J., S. Voss and D. L. Woodruff (2005). "Production Planning with Load Dependent Lead Times." *4OR: A Quarterly Journal of Operations Research* 3: 257-302.

Pritsker, A. A. B. and K. Snyder (1997). Production Scheduling Using FACTOR. *The Planning and Scheduling of Production Systems*. A. Artiba and S. E. Elmaghraby, Chapman and Hall.

Riano, G. (2003). Transient Behavior of Stochastic Networks: Application to Production Planning with Load-Dependent Lead Times. School of Industrial and Systems Engineering. Atlanta, GA, Georgia Institute of Technoogy.

Riano, G., R. Serfozo, S. Hackman, S. H. Ng, L. P. Chan, and P. Lendermann (2003). Benchmarking of a Stochastic Production Planning Model in a Simulation Testbed. Winter Simulation Conference.

Srinivasan, A., M. Carey, and T. E. Morton (1988). Resource Pricing and Aggregate Scheduling in Manufacturing Systems. Graduate School of Industrial Administration, Carnegie-Mellon University. Pittsburgh, PA.

Sterman, J. D. (2000). *Business Dynamics: Systems Thinking and Modeling for a Complex World*. New York, McGraw-Hill.

Tardif, V. and M. L. Spearman (1997). "Diagnostic Scheduling in Finite-Capacity Production Environments." *Computers and Industrial Engineering* 32: 867-878.

Uzsoy, R., C. Y. Lee and L. A. Martin-Vega (1992). "A Review of Production Planning and Scheduling Models in the Semiconductor Industry Part I: System Characteristics, Performance Evaluation and Production Planning." *IIE Transactions on Scheduling and Logistics* 24(47-61).

Voss, S. and D. L. Woodruff (2003). *Introduction to Computational Optimization Models for Production Planning in a Supply Chain*. Berlin, Springer-Verlag.

AUTHOR BIOGRAPHIES

SEZA ORCUN is an associate research scientist at the e-Enterprise Center at Discovery Park at Purdue University. He has completed BS (1994), MS (1995) and Ph.D. (1999) programs in Chemical Engineering at Bogazici University, Istanbul-Turkey. He joined to Purdue University as a post-doctoral research associate in early 1999 and promoted to a fulltime research associate appointment in early 2002 in the School of Chemical Engineering before accepting his current appointment in mid 2004. His research in scheduling and planning of process industries focuses on developing novel and practically usable scheduling and planning tools/environments, which can be used in daily decision making as well as in training programs for industrial practices. His affiliation with Laboratory for Extended Enterprises at Purdue (LEEAP) expands his research area and vision to supply chain modeling, design and management. His e-mail address is <sorcun@purdue.edu>.

REHA UZSOY is a Professor in the School of Industrial Engineering and Director of the Laboratory for Extended Enterprises at Purdue University. He holds BS degrees in Industrial Engineering and Mathematics and an MS in Industrial Engineering from Bogazici University, Istanbul, Turkey. He received his Ph.D. in 1990 from the University of Florida and joined the faculty of Purdue University the same year. His teaching and research interests are in production planning, scheduling, and supply chain management. He is the author of one book, an edited book, and over sixty refereed journal publications. He has also worked as a visiting researcher at Intel Corporation and IC Delco. His research has been supported by the National Science Foundation, Intel Corporation, Hitachi Semiconductor, Harris Corporation, Kimberly Clark, Union Pacific and General Motors. He was named a Fellow of the Institute of Industrial Engineers in 2005, Outstanding Young Industrial Engineer in Education by the Institute of Industrial Engineers in 1997 and a University Faculty Fellow by Purdue University in 2001, and has received both the A.A. B. Pritsker Award for Excellence in Undergraduate Teaching and the J. H. Greene Award for Outstanding Graduate Instructor (twice). He is currently serving on the Editorial Boards on *IIE Transactions on Scheduling and Logistics* and *Journal of Manufacturing Systems*. His e-mail address is <uzsoy@purdue.edu>.

KARL KEMPF is a member of the National Academy of Engineering, an Intel Fellow and an Adjunct Professor at Arizona State University. His research interests span the optimization of production and supply chain planning and execution in semiconductor supply chains including various forms of simulation. He can be contacted by e-mail at <karl.g.kempf@intel.com>.