Proceedings of the 2005 Winter Simulation Conference
M. E. Kuhl, N. M. Steiger, F. B. Armstrong, and J. A. Joines, eds.

LOT-SIZING WITHIN CAPACITY-CONSTRAINED MANUFACTURING SYSTEMS USING TIME-PHASED PLANNING

S. T. Enns
Pattita Suwanruji

Department of Mechanical and Manufacturing Engineering
University of Calgary
Calgary, Alberta
T2N 1N4, CANADA

ABSTRACT

Research on lot sizing has mostly assumed single echelon systems. Even when multiple echelon systems have been used, capacity constraints are seldom considered. However, in manufacturing capacity constraints can lead to significant queuing effects. Commonly used lot sizing policies like Lot-For-Lot (LFL) and Period Order Quantity (POQ) do not take these effects into account. This research compares these policies with a Fixed Order Quantity (FOQ) policy, within which lot sizes are based on minimizing estimated lot flowtimes at capacity-constrained machines. Simulation is used to study a small production and distribution network using time-phased planning. Results show that the FOQ policy performs better than both LFL and POQ when inventory levels and delivery performance are of concern.

1 INTRODUCTION

Time phased planning is common in manufacturing and distribution systems. Material Requirements Planning (MRP) logic is commonly used in batch manufacturing systems where capacity constraints are an important consideration. Distribution Requirements Planning (DRP) is similarly used for downstream material movement from the factory towards end users. If information systems can be integrated across manufacturing and distribution, MRP and DRP planning and control systems can also be integrated and fully centralized.

Different lot-sizing policies can be applied when using a time-phased replenishment strategy. Lot-for-Lot (LFL) is among the most popular with practitioners since it is simple and produces the least remnant work-in-process inventory (Ho, 1993). However, setup costs can be excessive if too many small lot sizes result. Fixed-Order-Quantity (FOQ) is another policy used extensively in practice due to its simplicity and lot size consistency (Haddock and Hubicki, 1989). While these rules may be justified for practical reasons, it has been argued that other lot-sizing policies are more theoretically sound. Some of these are based on optimization algorithms or heuristics that attempt to achieve the lowest total cost. This usually includes setup and inventory holding cost components. Such lot-sizing policies include Economic-Order-Quantity (EOQ), Least-Total-Cost (LTC), Silver-Meal (SM) and Wagner-Whitin (WW). A limited number of studies have reported comparisons of performance using such policies under time-phased replenishment. Bookbinder and Heath (1988) considered a multiple-level distribution system without capacity constraints. Brennan and Gupta (1993) considered an MRP system but did not explicitly include capacity constraints. Ho (1993) also considered an MRP system but not the costs associated with capacity constraints.

It can be argued that lot-sizing policies for systems with capacity constraints should take work-in-process (WIP) inventory into account. This inventory in queue is a function of utilization levels, lot interarrival time characteristics and lot service time characteristics. A limited number of studies have addressed this issue by using queuing relationships to determine lot sizes, often assuming relatively simple scenarios. Jönnson and Silver (1985) demonstrated that inventory in queue is an important component of costs in capacity-constrained systems. Lambrecht and Vandaele (1996) developed a search procedure to determine optimal lot sizes for the multi-item single location problem under GI/G/1 queuing assumptions. Lambrecht, Iven and Vandaele (1998) extended the investigation to look at the multi-item, multi-location problem in a job shop context. Hill and Raturi (1992) developed an approach, based on M/G/c queuing assumptions, to set reorder intervals for the POQ lot-sizing policy. Finally, Enns and Choi (2002) illustrated the use of lot sizes designed to minimize average lot flowtimes, based on GI/G/1 queuing assumptions, in an MRP system context. Studies making comparisons between lot-sizing policies with and without capacity constraint considerations seem to be lacking.

2 THE SIMULATION METHODOLOGY

In this study a previously developed test bed was used to run structured discrete-event simulation experiments comparing the performance of using different lot-sizing policies within a DRP/MRP system. This test bed was designed to be simple, flexible and transparent (Enns and Suwanruji, 2003). It consists of two main modules. The first is a simulator module based on ARENA® and containing generic code to model small supply chain scenarios. The second is a planning module based on an Excel workbook. It is used to specify the supply chain scenario, execute time-phased planning logic and collect performance statistics. Visual Basic for Applications® (VBA) is used within various macros in both the simulator and planning modules, as well as for dynamic communication between the two modules.

Two very important dimensions of performance relate to inventory levels and customer delivery performance. This research considers both dimensions. The item count across all echelons of the supply chain is used as the inventory measure and mean tardiness at the point of customer delivery is used as the delivery performance measure. Customer order tardiness is the amount of time an order is backordered. Orders delivered from stock are considered to have zero tardiness. It is assumed customers wish to have orders filled from stock and that orders placed during a stockout will be filled as soon as inventory is available.

It is desirable that the performance of replenishment systems is compared over a range of performance levels. Furthermore, it is well known there is a trade-off between inventory and delivery performance. Therefore, the inventory levels in the supply chain were changed incrementally during experimentation and the delivery performance at these various levels is observed. This was done by changing planned leadtimes within the DRP/MRP system. It is therefore possible to generate performance trade-off curves for different sets of experimental factors, as illustrated in Figure 1.

In this figure each curve represents the inventory-delivery performance trade-off for one set of experimental factors. For example, curve A might represent results using a Fixed Order Quantity (FOQ) lot-sizing rule while curve B might represent results using a Lot-for-Lot (LFL) rule. Curve A is preferable since less inventory is required for a given tardiness level. Conversely, curve A shows better delivery performance for a given inventory level. The benefit of using such trade-off curves are: 1) the dominant strategy is easily determined, 2) the conclusions do not depend on case-specific cost parameters and 3) the conclusions are valid over a wide range of service levels.

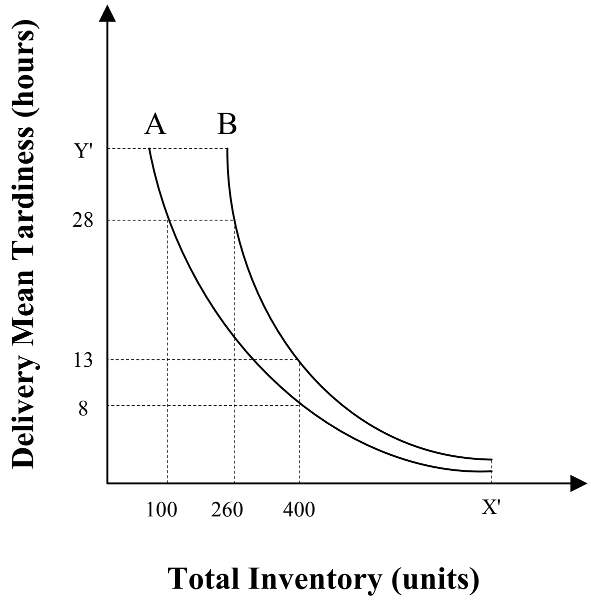

Figure 1: Inventory-Delivery Tardiness Trade-Off Curves

3 THE EXPERIMENTAL SCENARIO

The supply chain configuration used in this research is shown in Figure 2. The supply chain is composed of six locations. Two locations, L1 and L2, serve a distribution or retail function and are exposed to independent customer demand. These locations have finished goods storage but no capacity constraints. Locations L3 to L6 serve a production function. These locations may be considered to be capacity constrained if time delay operations are assumed. In this case storage of both work in queue and storage of processed parts are required. These storage requirements are indicated upstream and downstream from L3 to L6. None of the storage areas are assumed to have any space constraints.

The Bill-of-Distribution (BOD) and Bill-of-Material (BOM) shown in Figure 3 describe the structures dictating the flow of material. There are eight part types, P1 to P8. Locations L1 and L2 carry end items, P1, P2 and P7, exposed to customer demand. P1 and P2 are both derived from P3 and identify the same type of product stocked at different locations. P7 is derived from P6. Since P6 is also a component of P3, the parts going directly to L2 could be considered spare or repair parts. At L3, P3 is assembled from three P4, one P6 and one P8 parts. At L5, P6 is produced from two units of P5. At L4, P8 is produced from one P5 and P4 is produced from one unit of raw material RM4. At L6, P5 is produced from one unit of raw material RM4. Supplies of RM4 and RM5 are assumed to be unlimited.

Part types P1, P2 and P7 have average demands of 1000, 1000, and 1500 units per period, respectively. Periods are assumed to be one week in length, equal to five working days. Daily demand for end items follows a gamma distribution. Daily demand variation is determined on the basis of having a period demand coefficient of variation of 0.1. End-item demand is supplied from stock

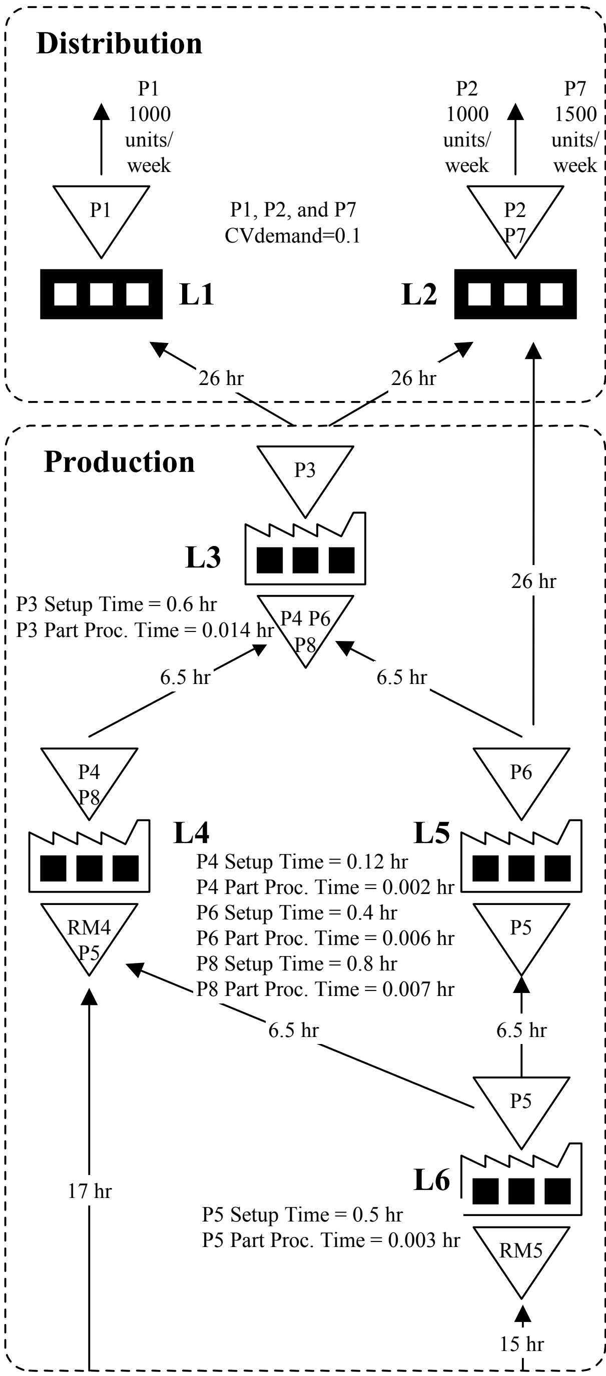

Figure 2: Configuration of the Supply Chain Network

to customers immediately. Unfilled demand is backordered and items are shipped as soon as inventory becomes available. Orders are filled on First-Come-First-Serve (FCFS) basis.

When there are capacity constraints, lots arriving at manufacturing locations must undergo a setup time and a lot processing time. Mean setup and part processing times for processed and assembled parts are displayed in Table 1.

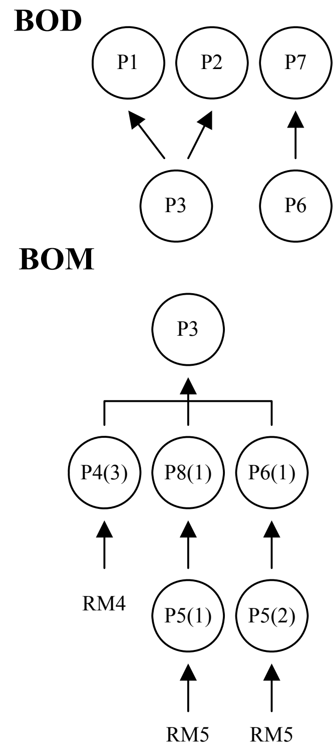

Figure 3: Bills of Distribution and Materials

Times are given in hours, using the assumption there are 40 hours per period (or 8 hours per day). The lot setup times are stochastic and follow a normal distribution with a coefficient of variation of 0.3. The lot processing times are deterministic and based on multiplying the lot size times the fixed part processing time. Processing of all lots in queue is based on FCFS.

Transit times, also shown in Table 1, are defined as the time to move an available lot of inventory from an upstream location to a downstream location. The transit times for all part types were assumed to be stochastic and follow an off-set-negative exponential distribution with a coefficient of variation of 0.1. No capacity constraints were assumed for inventory transportation. For all part types, it was assumed that the required lot-size order quantity was available from the upstream supplier before shipments could be released (i.e. lot splitting is not allowed). Furthermore, for assembly operations it was assumed that the required lot-size quantities of all components were available before any components were released for shipment. A common transit time was then applied to all components so arrival at the assembly location was simultaneous. The times shown in Table 1 are for all component lots going into each individual part type.

Replenishment planning was based on common DRP/MRP regeneration logic for time-bucketed systems. Planning was driven by a ten-period rolling horizon forecast for each independent demand part type. These fore casts were based on expected period demand and were therefore unbiased.

Table 1: Mean Setup, Part Processing and Transit Time

Part Type	Mean Setup Time (hr)	Part Processing Time (hr)	Mean Transit Time (hr)
P1	-	-	26.0
P2	-	-	26.0
P3	0.60	0.014	6.5
P4	0.12	0.002	17.0
P5	0.50	0.003	15.0
P6	0.40	0.006	6.5
P7	-	-	26.0
P8	0.80	0.007	6.5

The Master Schedule for the DRP/MRP system was based on order releases occurring once per day, which is equivalent to having five releases per period. The number of time buckets per period was assumed to be 20. Since a period was assumed to equal 40 hours, each time bucket was therefore equivalent to two hours. Orders for dependent demand parts could be released at the start of any time bucket. Further information on the DRP/MRP implementation and the logic used to control releases can be found in Suwanruji (2004).

4 LOT-SIZING PARAMETER SELECTION

In this research comparisons using Fixed-Order-Quantity (FOQ), Lot-for-Lot (LFL) and Period-Order-Quantity (POQ) policies were made. These represent diverse approaches to lot size selection. This section first describes the queuing approach used to obtain appropriate FOQ lot sizes. The FOQ lot sizes selected were then used to determine the number of time buckets of demand to include in orders, T_{POQ}, when using POQ. This approach was designed to obtain good performance while at the same time keeping comparisons across lot-sizing policies as fair as possible. The LFL policy is not considered in this section since it requires no parameter selection.

Lot-sizing relationships to minimize mean lot flowtimes or queue times at capacity-constrained machines have been developed in previous research. These are generally based on the restrictive assumption that interarrival times are independent. When lot interarrival times are assumed general, it is usually satisfactory to describe the distribution by the first two moments, the mean and standard deviation. In this case, GI/G/1 queuing approximations can be used to estimate steady-state performance. The following approximation is often suggested to estimate mean flowtimes, W_m, at a single machine m (Whitt, 1983).

$$W_m = W_{q,m} + \bar{x}_m = \bar{x}_m \frac{\left(c_{a,m}^2 + c_{s,m}^2\right)}{2} \frac{\rho_m}{1-\rho_m} + \bar{x}_m, \quad (1)$$

where W_q is the weighted mean time in queue, $\bar{x}$ is the weighted mean lot service time, c_a is the coefficient of variation for lot interarrival times, c_s is the coefficient of variation for lot service times and ρ is the machine utilization rate.

When the entities in queue represent lots of parts, the weighted mean lot service time, including setup times, for n part types processed on machine m is given by the following.

$$\bar{x}_m = \frac{\sum_{j=1}^{n} \frac{D_j}{Q_j}\left[\tau_j + \frac{Q_j}{P_j}\right]}{\sum_{j=1}^{n} \frac{D_j}{Q_j}}, \quad (2)$$

where j is the part type index, D_j is the average demand rate, Q_j is the part type lot size, P_j is the part processing rate, and τ_j is the lot setup time.

The utilization rate, including setup times, is then given by the following,

$$\rho_m = \sum_{j=1}^{n}\left[\frac{D_j}{Q_j}\left(\tau_j + \frac{Q_j}{P_j}\right)\right]. \quad (3)$$

If it is assumed the lot setup times and part processing times are deterministic, the coefficient of variation for the lot service times squared is expressed as follows,

$$c_{s,m}^2 = \frac{\sum_{j=1}^{n} \frac{D_j}{Q_j}\left[\tau_j + \frac{Q_j}{P_j}\right]^2 \left(\sum_{j=1}^{n} \frac{D_j}{Q_j}\right)^{-1}}{\bar{x}_m^2} - 1. \quad (4)$$

The objective is to solve for the values of the lot sizes, Q_j, that will minimize the lot flowtimes. The variables D_j, P_j and τ_j are assumed given or readily estimated in practice. In order to estimate c_a, the mean and standard deviation of interarrival times is required. The mean is easy to determine, based on given D_j and Q_j values. However, the standard deviation is harder to estimate. The standard deviation can be estimated from the observed interarrival times during a simulation run. However, these interarrival times are auto-correlated whereas Equation (1) is based on independent interarrival time assumptions (Enns and Li, 2004). Prior research has determined that using c_a values of 0.30 works well (Enns and Choi, 2002). This value is also used as a default in certain rapid modeling software (MPX User Manual, 1992) and was therefore selected for use in this research.

Once the variable values in Equations (1) to (4) have been estimated, the lot sizes that minimize average lot flowtimes can be solved for. Relationships to facilitate solution, based on differential equations, are given in Enns and Choi (2002). The lot sizes obtained using optimization techniques to minimize average lot flowtimes at capacity-constrained locations are given in Table 2. The shaded rows also show the lot sizes for the independent demand parts, P1, P2 and P7. These were set equal to one fifth of the average period (weekly) demand. Therefore the lot sizes correspond to the average MPS order release quantities on a daily basis, assuming five days per period.

POQ lot sizes are net requirements over a multiple number of time buckets. The decision parameter is the number of time buckets to include when aggregating requirements to make up one order. This parameter can be calculated using Equation 5. Note that in this study the lot size, Q_j, is based on the FOQ lot sizes calculated to minimize lot flowtimes.

$$T_{POQ,j} = \frac{Q_j}{D_j} * \frac{1}{p} \tag{5}$$

where $T_{POQ,\,j}$ is the number of time periods used in planning part type *j* orders, D_j is the average period demand for part type *j* and *p* is the size of the time buckets, in periods.

The periods of demand to include in orders for each part type are shown in the last column of Table 2. The calculation of the T_{POQ} parameters is based on rounding the value obtained using Equation (5) to an integer number of time buckets, assuming 20 time buckets per period.

Table 2: Lot Sizing Parameters

Part	Avg. Period Demand, *D*	Q_{FOQ} (units)	T_{POQ} (periods)
P1	1000	200	0.20
P2	1000	200	0.20
P3	2000	150	0.10
P4	6000	750	0.15
P5	9000	500	0.05
P6	2000	105	0.05
P7	1500	300	0.20
P8	2000	200	0.10

5 THE EXPERIMENTAL DESIGN

The experimental design consisted of two factors. The first factor was the demand pattern, which was run at two levels. The second factor was the lot-sizing policy. This was run at three levels and included the Fixed Order Quantity (FOQ), Lot-for-Lot (LFL) and Period Order Quantity (POQ) policies. The six combinations of factor settings resulting form a full-factorial design are summarized in Table 3.

Table 3: Experimental Design

Factor 1: Demand Pattern	Factor 2: Lot Sizing Rule		
	FOQ	LFL	POQ
Level	*	*	*
Seasonal	*	*	*

It is well known that DRP/MRP performs well when demand is seasonal if the seasonality can be accurately forecasted. The centralized, time-phased planning logic anticipates changes in requirements and releases orders to accommodate these anticipated changes. However, it is not well understood whether interaction effects between the demand pattern and the lot-sizing policy are significant. Therefore, both level and seasonal demand patterns were chosen for experimentation.

For the level demand pattern, the expected period demand was assumed to be stable through time for each end item. The expected demands were assumed to be 1000 units per period for P1 and P2 and 1500 units per period for P7. For the seasonal demand pattern, the demand of end items P1 and P2 were assumed to follow a sinusoidal pattern with a cycle length equal to 52 periods (1 year). The amplitudes of the expected demand patterns were set to 200 for P1 and 250 for P2, while the pattern lags were set at 0 and 26 periods respectively. This offset in demand patterns was assumed so that loading on the capacity constrained resources remained relatively constant through time. The expect demand pattern for P7 was assumed to remain stable at 1500 units per period. Figure 4 illustrates the expected period demand for the end items under seasonal demand. Actual period demands were assumed stochastic, as previously stated.

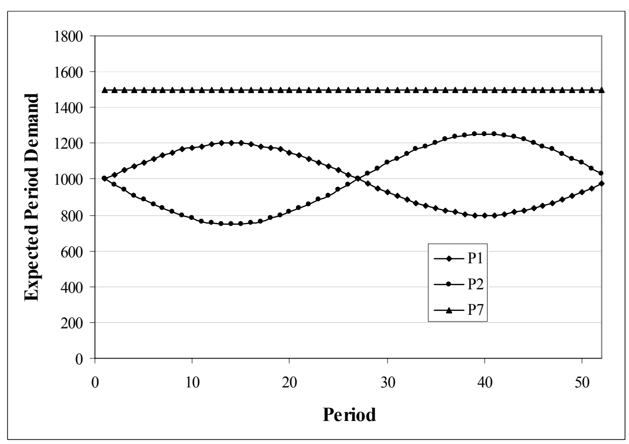

Figure 4: Exp. Period Demands with a Seasonal Pattern

The planned lead times for part type j, PLT_j, can be set equal to the expected replenishment time multiplied by a safety factor, and then rounded up to an integer number of time buckets.

$$PLT_j = \left\lceil \frac{RT_j}{p} SF_j \right\rceil p, \qquad (6)$$

where PLT_j is the planned lead time for part type j (periods), RT_j is the expected replenishment time for part type j (periods), SF_j is the safety factor for part type j and p is the size of the planning time buckets (periods). Initial planned leadtimes, based on a safety factor of 1.0, were 0.65, 0.65, 0.3, 0.5. 0.45, 0.20, 0.65 and 0.25 periods. Note that expected replenishment times included lot flowtimes and transit times.

The inventory-delivery performance trade-off curves were generated using simulation experiments in which the inventory at each combination of settings was gradually inflated. The inventory was inflated by adjusting the planned lead times using the safety factor (SF_i), as indicated in Equations (6). The safety factor was varied simultaneously across all replenishment loops from 1.0 upward in increments of 0.05 until 10 values were generated. In other words, 10 data points were used to generate a single trade-off curve.

Each trade-off curve was replicated five times. Since each curve required 10 simulation runs, the total number of runs for each of the six combinations of factor settings was 300. Each run was five years in length, with the first year being used for initialization. Common random numbers are maintained across factor combinations.

6 EXPERIMENTAL RESULTS

The tradeoff curves for delivery performance versus total inventory are shown in Figures 5 and 6. The points along these curves are based on the average results obtained across the five replications run at each combination of settings. Figure 5 shows the tradeoffs under level demand. Points along the curve moving toward the right represent the use of increasing safety factors, SF. It is obvious that the FOQ lot sizing policy produces superior performance since delivery performance is best for a given inventory level, or conversely, inventory is lower for a given level of delivery performance.

The results are similar under seasonal demand, as shown in Figure 6. It can be observed by looking at both Figures 5 and 6 that LFL and POQ perform very much the same. Even with the aggregation of demand over multiple time buckets, the behavior of POQ is similar to LFL since requirements in many time buckets are zero. It can further be observed by comparing Figures 5 and 6 that the demand pattern does not appear to impact performance much. In this research the shop load under seasonal demand does not change much through time since the demand patterns for different end items tend to offset each other, as shown in Figure 4. Furthermore, the forecast of demand is unbiased and since DRP/MRP anticipates changes in requirements, performance is not greatly affected by the demand pattern, regardless of the lot-sizing policy. Under these conditions any interaction effects between the demand pattern and the lot-sizing policy are either small or negligible.

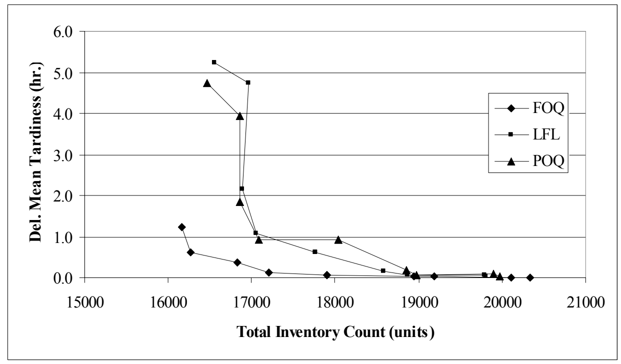

Figure 5: Level Demand

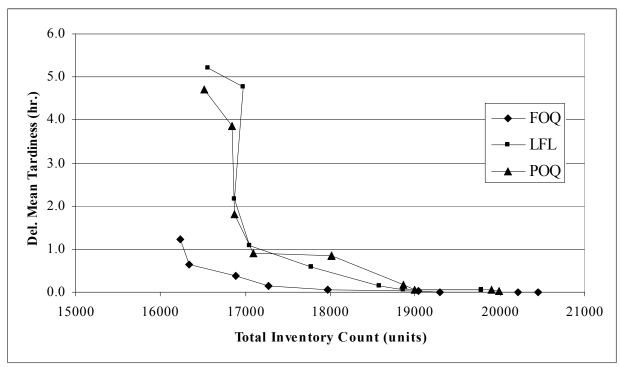

Figure 6: Seasonal Demand

The average lot sizes for each part type when using each of the lot-sizing polices are shown in Table 4. It can be noted that the lot sizes for all independent demand parts, shown as shaded rows, are roughly equivalent. This results from developing the Master Schedule on the basis of having lot sizes equal to the average daily demand. Using roughly the same Master Schedule to drive each of the planning systems ensures comparisons across different lot-sizing policies are kept fair.

The results in Table 4 indicate FOQ lot sizes at capacity-constrained locations are smaller. The performance with FOQ lot sizes is superior, as shown in Figures 5 and 6, even though more setups are being incurred. As expected, the POQ lot sizes are larger than the LFL lot sizes. The observed utilization rates at the capacity constrained locations agreed with the observed lot sizes. Under level demand and FOQ lot sizing, the utilizations at L3 to L6 were 0.898, 0.872, 0.857 and 0.898, respectively. When using LFL lot sizing these were 0.779, 0.773, 0.612 and 0.820 respectively, and when using POQ lot sizing these were 0.802, 0.791, 0.661 and 0.836 respectively. The utilization rates under seasonal demand were almost identical. It is interesting to note that the utilizations across the capacity-constrained locations are most uniform when using the FOQ policy.

Table 4: Average Lot Sizes by Part Number

Part Type	Level Demand			Seasonal Demand		
	FOQ	LFL	POQ	FOQ	LFL	POQ
P1	200	197	194	200	197	194
P2	200	197	194	200	197	194
P3	150	194	238	150	194	239
P4	750	822	895	750	823	896
P5	500	559	618	500	559	618
P6	105	172	238	105	171	238
P7	300	296	292	300	296	292
P8	200	234	268	200	234	269

The behavior was examined more closely by looking at the total number of parts at each of the capacity-constrained locations. Figure 7 shows the total number of parts on average under level demand. This figure includes the parts in queue and on the machines across all capacity-constrained locations. This inventory is not affected by the safety factor setting, unlike warehouse inventory on the downstream side of the location. Figure 7 shows that inventory levels are less for FOQ than for POQ and LFL. Results under seasonal demand were very similar.

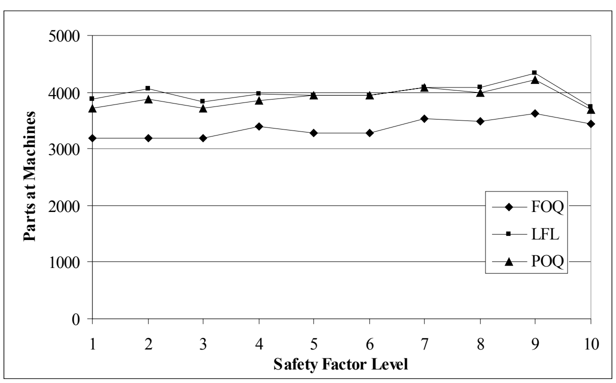

Figure 7: Level Demand

The average waiting time for components from the time of order release until the time they are available for shipment was also monitored. Figure 8 shows the average waiting times for the upstream components, in hours, across all part numbers except P4 and P5. These two part numbers are excluded since the gateway components, RM5 and RM6, are always assumed to be in stock. As expected, increasing the safety factor used in setting planned lead times reduces waiting times. Figure 8 again shows that FOQ results in the best performance. The lower waiting times for order releases to be filled indicates better timing and coordination with FOQ lot sizes.

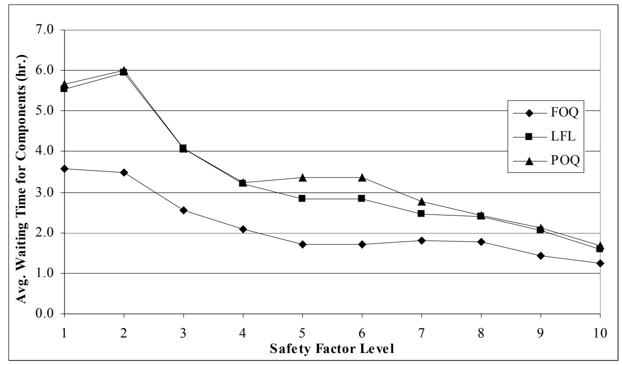

Figure 8: Level Demand

7 DISCUSSION AND CONCLUSIONS

The results of these simulation experiments clearly show that lot-sizing at capacity-constrained locations should take into account queuing considerations if the best delivery performance relative to inventory levels is to be obtained. Lot sizing rules based on requirements over a certain number of time buckets, propagated down through the planning records, do not take capacity constraints into account. Therefore, lot flowtimes at some of these capacity-constrained locations may be excessive.

A number of additional points warrant consideration and future research. First, in this research there were frequent occasions when more than one FOQ lot size was released at the same time, due to net requirements being greater than the lot size. In such cases a setup time was incurred for each lot, even if they were processed sequentially. Eliminating setups when processing lots of the same part type sequentially would improve the relative performance when using FOQ further.

A second observation was that the use of FOQ may allow more flexibility in selecting lot sizes at locations not having capacity constraints. The reason is that the lot sizes used downstream do not directly affect the lot sizes used upstream, as is the case with LFL and POQ. In other words, the propagation of lot sizes is independent from level to level and this may allow better average lot size combinations to be used. For example, it was observed that if the lot sizes for independent demand parts was reduced by 50% under FOQ lot sizing, the relative performance improvement for performance when using FOQ was even greater (Suwanruji, 2004).

A third observation was that scrap may also affect the relative performance of the lot-sizing policies. It may be that FOQ lot sizing is more robust to parts being scrapped since requirements are not propagated over a fixed number of time buckets. In this research no scrap was assumed. Further investigation is required to more fully understand the nature of these behaviors.

ACKNOWLEDGMENTS

This research was supported in part by a grant from the National Science and Engineering Research Council (NSERC) of Canada.

REFERENCES

Bookbinder, J. H. and D. B. Heath. 1988. Replenishment analysis in distribution requirements planning. *Decision Sciences*, 19(3), 477-489.

Brennan, L. and S. M. Gupta. 1993. A structured analysis of material requirements planning systems under combined demand and supply uncertainty. *International Journal of Production Research*, 31(7), 1689-1707.

Enns, S. T. and S. Choi. 2002. Use of GI/G/1 queuing approximations to set tactical parameters in the simulation of MRP systems. In *Proceedings of the 2002 Winter Simulation Conference*, ed. E. Yucesan, C.-H. Chen, J. L. Snowdon and J. M. Charnes, 1122-1129. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.

Enns, S. T. and P. Suwanruji. 2003. A simulation test bed for production and supply chain modeling, *Proceedings of the 2003 Winter Simulation Conference*, S. Chick, P.J. Sanchéz, S. Ferrin, and D.J. Morrice, Ed., 1174-1182. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.

Enns, S. T. and L. Li. 2004. Optimal lot-sizing with capacity constraints and auto-correlated interarrival times. *Proceedings of the 2004 Winter Simulation Conference*, R. G. Ingalls, M. D. Rosetti, J. S. Smith and B. A. Peters, Ed., 1073-1078. Piscataway, New Jersey: Institute of Electrical Engineers.

Haddock, J. and D. E. Hubicki. 1989. Which lot-sizing techniques are used in materials requirements planning?. *Production and Inventory Management Journal*, 30(3), 53-56.

Hill, A. V. and A. S. Raturi. 1992. A model for determining tactical parameters for material requirements planning systems. *Journal of the Operational Research Society*, Vol. 43, 605-620.

Ho, C. 1993. Evaluating lot-sizing performance in multi-level MRP systems: A comparative analysis of multiple performance measures. *International Journal of Operations and Production Management*, 13(11), 52-79.

Jönsson, H. and E. A. Silver. 1985. Impact of processing and queueing times on order quantities. *Material Flow*, Vol. 2, 221-230.

Kelton, W.D., R.P. Sadowski and D.T. Sturrock. 2004. *Simulation with Arena*, 3rd Ed., McGraw-Hill Co.

Lambrecht, M. R. and N. J. Vandaele. 1996. A general approximation for the single product lot sizing model with queueing delays. *European Journal of Operational Research*, Vol. 95, 73-88.

Lambrecht, M. R., P. L. Ivens and N. J. Vandaele. 1998. ACLIPS: A Capacity and Lead Time Integrated Procedure for Scheduling. *Management Science*, Vol. 44, 1548-1561.

MPX User Manual. 1992. Burlington, Massachusetts: Network Dynamics Inc.

Suwanruji, P. and S. T. Enns. 2004. Evaluating the performance of supply chain simulations with tradeoffs between multiple objectives. In *Proceedings of the 2004 Winter Simulation Conference*, R. G Ingalls, M. D. Rosetti, J. S. Smith and B. A. Peters, Ed., 1399-1403. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.

Suwanruji, P. 2004. Replenishment planning and control in supply chain management, Unpublished dissertation, Department of Mechanical and Manufacturing Engineering, University of Calgary.

Whitt, W. 1983. The Queueing Network Analyzer. *The Bell Systems Technical Journal*, 62(9), 2779-2813.

AUTHOR BIOGRAPHIES

SILVANUS T. ENNS is an Associate Professor at the University of Calgary, Canada. He received his PhD from the University of Minnesota. His research interests lie in the development of algorithms to support enhanced MRP performance as well as various aspects of job shop, batch production and supply chain modeling and analysis. His email address is enns@ucalgary.ca.

PATTITA SUWANRUJI recently completed her PhD at the University of Calgary, Canada. She previously received a BEng in Chemical Engineering from Kasetsart University and a MEng in Industrial Engineering from Chulalongkorn University, both in Bangkok, Thailand. Her research lies in the modeling and analysis of supply chains. Her email is psuwanru@ucalgary.ca.