SIMULATING ALTERNATIVE PRODUCTION SCHEDULES WITH VARIABLE TECHNOLOGY

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ABSTRACT

This article studies different sequencing and inventory rules in a manufacturing environment with nonlinear technological coefficients and stochastic demand. Multiple products require setup on a single machine and setup time and setup cost decrease with repeated setups. Furthermore, setup operations for different products have common components and an item can be benefited by a setup operation of another item. The single-level, multi-item lot size model is used to model the production environment. The learning curve is used to represent this decrease in setup time with repeated setups. The learning transmission between items affects the scheduling of the products and the resulting model considers simultaneous decisions about lot sizing and sequencing in a nonlinear formulation with a stochastic component. The problem is formulated and a simple production policy is simulated. Two sequencing rules and four inventory rules are examined. A simulation experiment of 6400 runs is studied and the results are analyzed.

INTRODUCTION

The lot size problem has received considerable attention in recent years. Wolsey [12] looks at the history of the single-item, uncapacitated lot-sizing problem and discusses extensions and new results that have been obtained in recent years. In a review article on heuristics for the multi-item, single-level capacitated dynamic lot-sizing problem, Maes and Van Wassenhove [7] consider the mathematical programming formulation with linear setup costs and negligible setup time. They indicate that an interesting change would be to include setup times which would make the capacity constraint non-linear and they give an example of an industrial project in which the production rates for individual items increase considerably over time due to technological improvements. The power function depicting setup learning (or improvement) can be used to represent such nonlinear technological coefficients.

The lot-sizing problem with setup learning has been studied for the case of unrestricted capacity [5] [1]. Rachamadugu [9] addresses the uncapacitated single product model with setup learning and develops a policy that sets the current lot size such that the current setup cost equals the holding cost for the current lot. He calls it the myopic policy. He shows that the number of setups in the myopic policy is at most one greater than the optimal number of setups and the average performance of the policy is good. A heuristic for the single-level, multi-item capacitated lot sizing problem with nonlinear setups was developed by Pratsini [8]. The optimal solution could be obtained for small problems and was used to test the efficiency of the heuristic. Transmission of learning between products was considered and demand was assumed to be dynamic but deterministic. The heuristic was based on the comparison of setup and inventory costs when making decisions on whether to produce or use inventory to satisfy demand. Learning complementarity was incorporate, and similar to Rachamadugu′s myopic approach, the heuristic performed very well and produced schedules with costs close to the optimal ones. This work relaxes the assumption of known demand, as in many manufacturing situations the exact value of demand is not known, even though an approximate value can usually be estimated. Such a scenario is appropriate for automated manufacturing environments where learning takes place in the setup of operations. Suzaki [10] describes methods for reducing setups and factors that contribute to learning transmission between products.

The model formulation is given in the next section, followed by the a description of the simulation model and a discussion of the scheduling and inventory rules used. The simulation results are given in the last section.

MODEL FORMULATION

Maes and Van Wassenhove [7] and Dixon and Silver [3] give the mathematical programming formulation of the multi-item, single-level, capacitated lot-sizing model with dynamic demand and time varying capacity. Their formulation is extended to include setup time in the capacity constraint, and incorporate setup learning in the objective function and capacity constraint. Furthermore, from Pratsini [8], the learning transmission between products can be represented by α_{im}. Whenever item m has a setup, another item i moves along its learning curve by a factor of α_{im}, where $0 \leq \alpha_{im} \leq 1$. A value of 0 indicates that there is no cross learning, while a value of 1 indicates that the two processes are identical. This factor is similar to the k parameter used by Chen [2] in modeling complementarity of worker learning. However, unlike the k parameter, α_{im} is not inversely proportional to α_{mi}. Furthermore, it is not symmetrical, $\alpha_{im} \neq \alpha_{mi}$, and $\alpha_{im} = 1$ when i = m. The sequencing of products can affect the setup cost of an item since the setup cost of the item can decrease if other products are produced first in that period. Model (LSL) in [8] gives the simultaneous problem of lot sizing, sequencing and cross learning. The demand parameter, however, is now stochastic, and a mathematical programming approach is not applicable.

SIMULATION MODEL

In a production situation with multiple products competing for a limited amount of capacity, and setup learning taking place, one must decide which products to produce in a period, the production sequence of these products and whether to produce any units to inventory. In the scenario under study, it is assumed that even though future demands have a known mean value, their specific values are unknown. The process in model (LSL) is characterized by n learning curves, one for each item, and as setups take place, the process moves along the curves. A simple production strategy is considered, where in every period production only takes place for those items whose inventory is not enough to satisfy demand. Two sequencing rules (SEQ) were considered in the experiment: (a) sequence is random (SEQ = 0) and, (b) items with lower setup costs are produced first (SEQ = 1). In period j the anticipated setup cost for item i is given by,

$$A = s_i\{[\sum_{m\in N} \alpha_{im}(R_{m,j-1} + Q_{mij}) + 1]^{B_i} - [\sum_{m\in N} \alpha_{im}(R_{m,j-1} + Q_{mij})]^{B_i}\} \quad (1)$$

where s_i is the first setup cost for item i, R_{mj} is the cumulative number of setups of item m in period j, and Q_{mij} is a binary variable considering the sequencing of the products, and is equal to 1 if item m is produced before item i in period j. B_i is the learning parameter for item i. The equation is recalculated every time an item is selected for the sequence. The first time equation (1) is calculated for period j no cross-learning takes place, thus all Q_{mij} variables are set equal to zero. The item with the lowest value is produced first. Equation (1) is then recalculated, for the remaining items, with the appropriate Q_{imj} variables being equal to 1 and thus considering cross-learning, and the item with the new lowest value of A is produced next. This continues until all items have been considered. By producing the item with the lowest anticipated setup cost first, costlier items are allowed to move further along their learning curve, due to cross learning, and thus lower their setup cost for that period.

The first sequencing policy is easy to implement and is usually applied in situations where the person in charge is unaware of any setup reductions due to learning. The second policy requires some calculations in order to calculate the setup cost of each item in a period and takes into consideration the benefits of learning.

After the production and sequencing decisions are taken, the inventory issue is addressed (INV). If there is any capacity left in a period that capacity can be used to produce units to inventory. Four inventory alternatives are considered: (a) available capacity at the end of a period is equally divided among items that are produced in that period (INV = 0), (b) available capacity is proportionally divided among items based on their setup cost (INV = 1). Only items produced in that period are considered. The third alternative (c) is similar to the second one having the capacity being divided proportionally based on the ratio of setup cost to holding cost (INV = 2). Finally, the fourth alternative (d) does not allow inventory to be produced in any period, thus follows the "zero inventory" policy (INV = 3).

For the first three rules, inventory can increase dramatically in the last periods when only a few products are produced and remaining capacity is allocated to the produced items. This can create huge inventories at the end of the planning horizon. To alleviate the problem, inventory for a product in period n is restricted to (average demand)*(t+1-n), where t is the last period in the planning horizon. Even though the actual demand for a period is not known, the average value is usually known, and the above expression allows the inventory at the end of the period t to be about equal to the average demand. The fourth inventory rule is only feasible when available capacity is not very restrictive and allows a lot for lot production for every item.

A model simulating the two sequencing rules and four inventory rules was written in FORTRAN. Two values for number of products, setup cost, setup time, demand variability and capacity were considered. The data for the problems were generated using Leschke's parameters [6]. Some of the parameters were adjusted for the type of problem. There is a total of 32 combinations of the various parameter levels. For each combination 2 sequencing rules and 4 inventory rules were applied. This brings the total to 256 problems. Furthermore, 25 replications were run for each of the 256 combinations, giving a total of 6200 runs to be analyzed. For each run three factors were used to evaluate the results. Cost (COST) was the primary factor of interest in comparing the performance of the different sequencing and inventory rules on the various scenarios. Effective learning rate (ELR) was determined as the last setup cost over the first setup cost for a product, and was the second factor used in the analysis. This factor determines how far along the learning curve the products have moved. Finally, the average number of setups (SETUPS) was used as another factor. The latter two factors are related. As the number of setups increases effective learning rate decreases.

SIMULATION RESULTS

The same random number stream was used in generating each replication for each combination and the results were analyzed using the approach of Kannan and Ghosh [4]. An Analysis of variance was performed separately on the eight-product and sixteen-product problems. Most of the results for the two levels of number of products were similar. It is worth noting that the sequence of production was significant at the 2% level for the 8-product case, however, it was not significant for the 16-product case. This can be explained as follows: when a large number of products is produced, the sequence of production becomes irrelevant as many setups take place in a period, and ultimately all products move along their learning curve and benefit from learning. However, when a few products are considered, the sequence can seriously affect the cost as there are not many opportunities for a product to move along its curve. It is also interesting to note that sequencing is significant for effective learning rate and the number of setups in the 8-product case, but it is only significant for the number of setups in the 16-product case.

Tables comparing the four inventory rules under the two sequencing alternatives for the 16-product case were constructed. The tables indicate that a lot for lot production is the best inventory policy as far as cost is concerned. However, as mentioned earlier, this policy is only viable when capacity is not too restrictive and allows the production of all products in every period. When capacity is limited and carrying inventory is necessary in order to have feasible production schedules, a simple approach of equally dividing available capacity between items produced in a period seems to outperform the more involved alternatives of dividing the capacity based on setup cost and inventory cost.

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