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RESEARCH NOTE

The Use of Switching Point and Protection Levels to Improve Revenue Performance in Order-Driven Production Systems

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ABSTRACT

In a multiproduct order-driven production system, an organization has to decide how to selectively accept orders and allocate capacity to these orders so as to maximize total profit (TP). In this article, we incorporate the novel concept of switching point in developing three capacity-allocation with switching point heuristics ($CASP_{a-c}$). Our analysis indicates that all three CASP heuristics outperform the first-come-first-served model and Barut and Sridharan's dynamic capacity-allocation process (DCAP) model. The best model, $CASP_b$, has an 8% and 6% average TP improvement over DCAP using the split lot and whole lot policies, respectively. In addition, $CASP_b$ performs particularly well under operating conditions of tight capacity and large price differences between product classes. The introduction of a switching point, which has not been found in previous capacity-allocation heuristics, provides for a better balance between forward and backward allocation of available capacity and plays a significant role in improving TP.

Subject Areas: Capacity Allocation, Order-Driven Production Systems, Protection Level, Revenue Management, and Switching Point.

INTRODUCTION

Revenue management originated in the airline industry and is aimed at solving the allocation of airplane seats with different fares (Belobaba, 1989; Pfeifer,

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1989; Curry, 1990; Weatherford & Bodily, 1992; Williamson, 1992; Belobaba & Weatherford, 1996). After more than four decades of development, revenue management techniques have been successfully applied to a variety of industries to enable an organization "to sell the right products to the right customer at the right time for the right price so as to maximize revenue" (Cross, 1997, p. 4). Examples of revenue management applications include car rentals (Geraghty & Johnson, 1997), hospitality management (Baker, Murthy & Jayaram, 2002; Kimes & Thompson, 2004), health care (Chapman & Carmel, 1992), management of public parks (Nautiyal & Chowdhary, 1975), broadcasting and advertising (Cross, 1997), E-commerce (Boyd & Bilegan, 2003), and Internet-based auctions (Baker & Murthy, 2002, 2005).

Early studies in the area of capacity allocation for the make-to-order production environment include Balakrishnan, Sridharan, and Patterson (1996) and Patterson, Balakrishnan, and Sridharan (1997). Their models optimally allocate the available capacity to different products or customers based on their revenue as well as delivery priority. One of the key challenges is to efficiently match capacity with demand, especially when it is difficult to increase capacity. Harris and Pinder (1995) present two models to solve the pricing and capacity-allocation problems for an order-driven production system with two classes of orders. Sridharan (1998) applies the concept of perishable asset revenue management to a tightly constrained capacity system with competing classes of products and/or customers. Balakrishnan et al. (1996) analyze a production system with two classes of products in the fashion industry and propose a heuristic capacity-allocation model under stochastic demands. Deng, Wang, Leong, and Sun (2008) present a marginal revenue-based capacity management (MRBCM) model that "generates order acceptance policies that allocate available capacity to higher revenue generating market segments" (2008, p. 737). The MRBCM model incorporates a unique opportunity cost estimation logic that has resulted in improved performance over existing models in the literature. Barut and Sridharan (2005) apply the dynamic capacity-allocation process (DCAP) technique to an order-driven production system in the fashion industry and show that it performs better than the first-come-first-served (FCFS) policy in a variety of scenarios.

The objective of this article is to develop a heuristic for allocating capacity in an order-driven system, which can improve performance over Barut and Sridharan's (2005) benchmark DCAP model. Our contribution in developing the heuristic is the inclusion of a switching point, a simple concept not found in previous models reported in the revenue management literature. However, the notion of a switching point has already been used to address many other management problems. For example, Amit (1986) investigates the petroleum producer's optimal switching policies from primary to secondary recovery. Thomke (1998) studies the switching between different "modes" of a given experiment in new product design to reduce the development cost and time. Berman, Wang, and Sepna (2005) examine the optimal switching points of cross-trained workers between the front room and back room to minimize the expected customer waiting time in a retail service facility. We postulate that the introduction of a switching point in the capacity-allocation model will provide a better balance between forward and backward allocation resulting in improved utilization of available capacity and performance.

CAPACITY ALLOCATION WITH SWITCHING POINT (CASP) HEURISTICS

For the sake of comparison, we utilize an order-driven production environment similar to the one introduced in Barut and Sridharan's (2005) study. Each customer order is characterized by a product class, an order size, and a due date. The system is capable of producing three classes of products: class 1 with the highest profit, class 2 with medium profit, and class 3 with the lowest profit. The profit derived from per unit capacity to produce class i products is P_i ($i = 1, 2, 3$), where $P_1 > P_2 > P_3$. We have a continuous time horizon (T), which consists of k periods. In each of these periods, the total available capacity is C.

Orders of class i products arrive in accordance with a nonhomogenous Poisson process, at a rate that is linearly decreasing with time such that $\lambda_{it} = (1.5 - \frac{t}{T})\bar{\lambda}_i$, $t = 0,1,\ldots,T$, where $\bar{\lambda}_i$ = average arrival rate (Balakrishnan et al., 1996; Barut & Sridharan, 2005). The order size of class i products follows a truncated normal distribution, with mean μ_i and standard deviation σ_i ($i = 1, 2, 3$). Note that the order size is nonnegative; if it is negative, regenerate a new random number. The due date of each order is uniformly distributed on the interval, $[\max(t, (\frac{k}{2} + 1)), k]$, where t is the arrival time of the order and k is the number of periods in the time horizon T. We do not allow any tardiness but products can be finished early without penalty. The capacity in each period is fixed and any unused capacity is lost. In addition, when an order is received after the start of a period, only the capacity available from the moment of its arrival time until its due date can be used.

We introduce the concept of switching point in developing three CASP heuristics to further improve performance. To test the significance of a switching point, production is restricted to the second half of the planning period. This assumption is not unusual in the fast-moving fashion industry where orders are back scheduled from the due date to meet current market needs and to minimize inventory holding cost. For example, The Limited commits to an order from Li & Fung for 100,000 garments several months ahead of the season to lock up capacity, but style or colors are only provided five weeks before the delivery date (Magretta, 1998). The three CASP models as well as a FCFS with switching point heuristic are discussed next.

$CASP_a$

Our first heuristic, $CASP_a$, is as follows: Set $t = (\frac{k}{2} + 1)$ as the switching point, where k = number of periods in the time horizon. With this allocation heuristic, orders accepted in the first $k/2$ periods can only be scheduled for the start of production in period $(\frac{k}{2} + 1)$ and beyond. Orders for the three classes of products can be accepted and produced in the periods from $(\frac{k}{2} + 1)$ to k. For orders that arrive before the switching point, reserve some capacity for each class of orders except the lowest one; otherwise, use the FCFS rule where orders are accepted in the order they arrive. For the accepted orders, if they arrive before the switching point, then use backward allocation; otherwise, use forward allocation.

Because the class i orders arrive in accordance with a nonhomogenous Poisson process with decreasing rate (i.e., the arrival rate in period t is $\lambda_{it} = 1.5\bar{\lambda}_i(1 - 2t/3T)$, where $t = 1, 2, \cdots T$), then the percentage of orders arriving in interval $[0, t]$ with respect to total arriving orders is $= \frac{\frac{1}{2}(\lambda_{it}+\lambda_{i0})t}{\frac{1}{2}(\lambda_{iT}+\lambda_{i0})T} = \frac{t(3T-t)}{2T^2}$, where $t = k/2$ and $T = k$. Next, we set a static protection level for each class of orders according to its percentage of expected orders.

The protection level for the class i orders is computed as follows:

$$PL_1(i) = \min\left\{\frac{t(3T-t)}{2T^2}U_T - \sum_{j=1}^{i-1} PL_1(j), \frac{t(3T-t)}{2T^2}\mu_i\overline{\lambda_i}\right\}, \quad i = 1, 2, 3$$

$CASP_b$

Our second heuristic, $CASP_b$, which is a modified version of $CASP_a$, is described as follows: Set $t = (\frac{k}{2} + 1)$ as the switching point. For orders that arrive before this point, use $CASP_a$; otherwise, use the modified FCFS mechanism, which is described as follows: when $CT \leq X$, where X = capacity tightness level determined empirically from an earlier experiment that provides the best performance ($X = 0.7$), for the class 3 product order, if there is no available capacity in the subsequent E_3 periods after its arrival, then refuse this order; for the class 2 product order, if there is no available capacity in the subsequent E_2 period after its arrival, then refuse this order.

Note that E_i is the constrained time period to accept the order for product class i and is calculated as follows:

$$E_i = \sqrt{k/[2^*(i-1)^*(i+1)]}$$

where i (class of orders) = 1,2,3 and k = total number of periods

For example, when $k = 450$ and $i = 2$, this value equals $\sqrt{450/[2^*(2-1)^*(2+1)]} = \sqrt{450/6} = 8.66$ and can be rounded normally to 9; when $i = 3$, this value equals $\sqrt{450/[2^*(3-1)^*(3+1)]} = \sqrt{450/16} = 5.30$ and can be rounded normally to 5. Note that when $i = 1$, this value equals infinity, corresponding to zero constraint for a class 1 order. Note that class 1 products have the highest profit and therefore there should be no constraint on accepting this class of orders.

Once an order is accepted, the allocation mechanism is the same as $CASP_a$. If $CT > X$, then use FCFS.

$CASP_c$

The heuristic, $CASP_c$, is provided below: Set $t = (\frac{k}{2} + 1)$ as the switching point. For orders that arrive before this time, use $CASP_a$; otherwise, reserve some capacity for each class of orders except the lowest one. Unlike $CASP_a$, the protection level for a class i order is:

$$PL_2(i) = \min\left\{\left[1 - \frac{t(3T-t)}{2T^2}\right]U_T - \sum_{j=1}^{i-1} PL_2(j), 0.5\left[1 - \frac{t(3T-t)}{2T^2}\right]\mu_i\overline{\lambda_i}\right\}, \quad i = 1, 2, 3.$$

Once an order is accepted, the allocation mechanism is the same as $CASP_a$.

First-Come-First-Served with Switching Point Policy

Although the FCFS policy is quite simple and easy to implement, it may not perform as well as other mechanisms. When the capacity is fairly limited and we selectively accept orders according to their respective revenue, there is a good probability of obtaining higher performance. Because the *CASP* models include a switching point, we now incorporate this element into the FCFS model, which is referred to as $FCFS_m$. We explain the model below:

For each accepted order, if its arrival time is less than $t = (\frac{k}{2} + 1)$ then use backward allocation to accommodate the order; otherwise, use forward allocation.

OPERATING AND EXPERIMENTAL ENVIRONMENT

We utilize the operating environment in Barut and Sridharan's (2005) study, which was motivated by an earlier experience at a medium-sized apparel company producing a variety of high-fashion apparel for women. Sport Obermeyer would be an example of a company in this industry. The operating factors, order processing policies, performance metrics, and number of scenarios tested are presented next.

Operating Factors

Profit attractiveness (AF) captures the rate of change in profit contributions of the different product classes. We consider five levels of AF: 0.5, 0.6, 0.7, 0.8, and 0.9. An AF value of 1 means all three product levels have the same profit. A smaller value of AF implies a larger difference in price between the product classes. The relative profitabilities among different classes are denoted as P_i/P_{i+1}, $i = 1, 2$. To reflect the diversity of relative profitability differences, we consider the following three patterns: (i) decreasing relative profitability (DRP): $P_2 = P_1 \times AF^2$ and $P_3 = P_2\sqrt{AF}$; (ii) stable relative profitability (SRP): $P_2 = P_1 \times AF$, and $P_3 = P_2 \times AF$; and (iii) increasing relative profitability (IRP): $P_2 = P_1\sqrt{AF}$ and $P_3 = P_2 \times AF^2$. Let $P_1 = 1$, then P_2 and P_3 can be determined by the above AFs and relative profitability patterns.

Capacity tightness (CT) is the ratio of total available capacity and total expected demand over the time horizon. CT is also examined at five levels: 0.5, 0.6, 0.7, 0.8, and 0.9.

Order size structure (OSF) represents order size patterns for the different product classes. The mean order size for product class i is μ_i. Let $OSF = \mu_i/\mu_{i+1} = \mu_{i+1}/\mu_{i+2}$. We investigate the OSF at two levels: 0.75 and 1.25. For example, if $\mu_3 = 6$, then μ_1 and μ_2 can be determined using the OSF equation.

Order rate structure (ORF) is defined as the ratio of the average order rate of two classes, $ORF = \bar{\lambda}_i/\bar{\lambda}_{i+1} = \bar{\lambda}_{i+1}/\bar{\lambda}_{i+2}$. We examine ORF at levels of 0.75 and 1.25.

Demand variation (CV) is determined by the ratio of standard deviation to the mean of the demand. We assume the three product classes share the same CV, which varies at two levels, 0.25 and 0.5.

Order Processing Policies

There are two order-processing policies: (i) Whole lot order processing where each order must be processed in one lot, and (ii) Split lot order processing where each order can be split into several lots and processed between the arrival date and due date. The other parameter settings are: order size = 6, capacity/period = 24, and number of periods (k) = 450. In this environment, most orders can be processed within one period. However, when we have a large number of periods where the remaining capacity is small, the split order processing approach can more efficiently utilize the available capacity.

Performance Metrics

The primary performance metric is total expected profit, which is calculated as $\sum_{i=1}^{3} P_i . O_i$, where P_i = profit per unit capacity allocated to product class i and O_i is the total demand for product class i. Another performance measure is capacity utilization (CU), which is defined as the ratio of the total capacity used to the total fixed capacity available over the planning horizon.

Number of Scenarios Tested

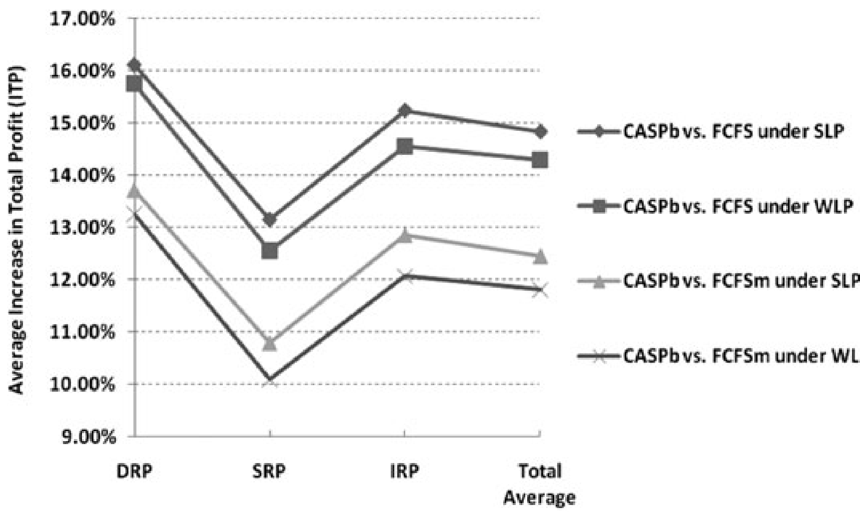
The total number of different scenarios tested is 200, and is derived from five levels of AF, five levels of CT, two levels of OSF, two levels of ORF, and two levels of CV.

RESULTS

We compare the performance of the CASP models with both the FCFS_m and FCFS models. The results of the simulation analysis show that all three CASP models outperform the FCFS policy in terms of percentage increase in total profit (ITP) but $CASP_b$ has the best performance. What is interesting is that $CASP_b$ showed a positive ITP over FCFS for all 200 scenarios tested using both the split lot and whole lot policies. In addition, $CASP_b$ also showed a slight increase of 1.2% in CU over the FCFS model using the split lot policy and a marginal increase of 0.2% in CU over the FCFS model using the whole lot policy. This indicates that $CASP_b$ is a robust heuristic that outperforms the FCFS model under a wide variety of operating conditions tested. Using $CASP_b$, not only do we see an ITP but we also observe a slight improvement in CU. Details of the analysis are available from the authors on request. This result may be explained as follows: Because the number of orders arriving after the switching point is much less than those that arrived before, it is appropriate to use FCFS after the switching point; before the switching point, refusing a certain amount of orders of lower profit classes when the capacity is tight will allow some capacity to be available for orders of higher profit classes and thus increase the total revenue. Because $CASP_b$ has the best performance, we show only the performance of $CASP_b$ over the FCFS under the split lot and whole lot policies in Figure 1.

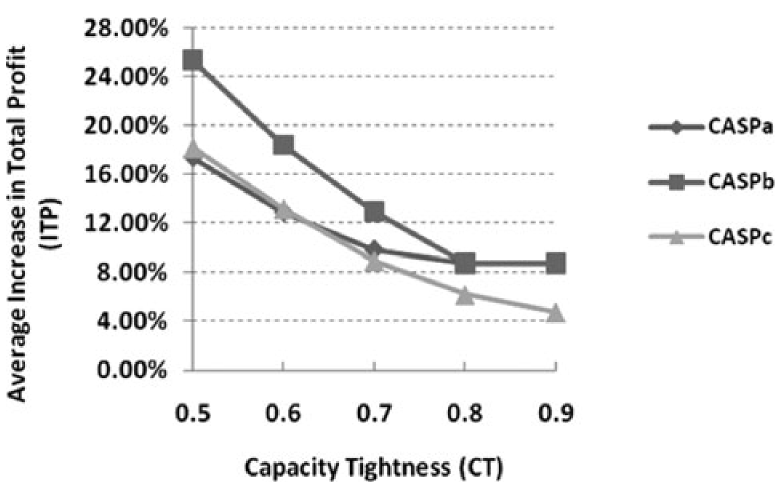
We use analysis of variance (ANOVA) to analyze the simulation results. Because $CASP_b$ has the best performance, the experimental variable is TP($CASP_b$)/TP(FCFS_m) and we compare performances between $CASP_b$ and

Figure 1: Performance of $CASP_b$ over four different scenarios. SLP = split lot policy; WLP = whole lot policy.



SLP = split lot policy; WLP = whole lot policy

Figure 2: Simulation results for different CTs under the split lot policy.



$FCFS_m$. Under the whole lot policy and split lot policy, both CT and AF are significant at the 5% level whereas the interaction effects among ORF, OSF, and AF are not significant. The ANOVA results are available from the authors on request. Because the impacts of CT and AF are the most significant, we will discuss these results further.

From Figures 2 and 3, we find that: (i) With a smaller CT, which corresponds to a tighter capacity situation, the improvements of the three *CASP* models over

Figure 3: Simulation results for different CTs under the whole lot policy.

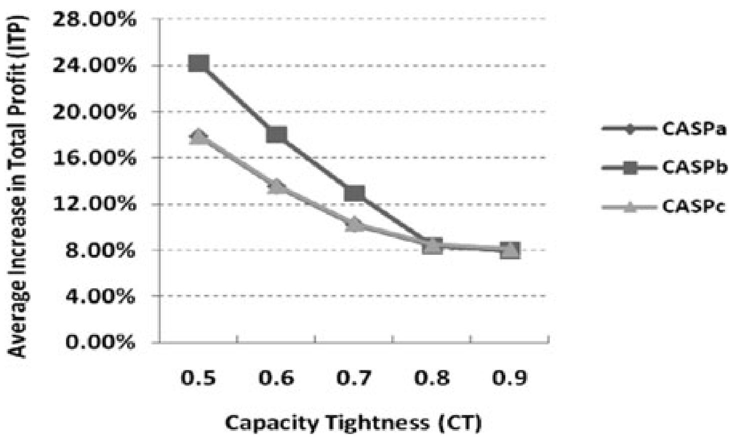
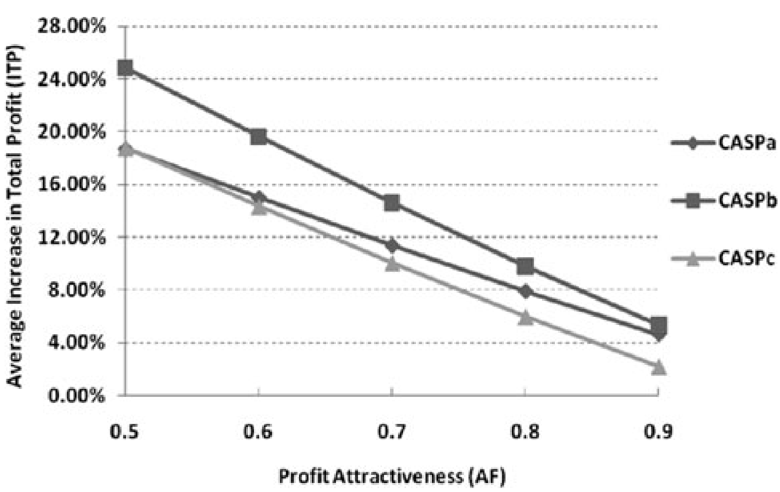


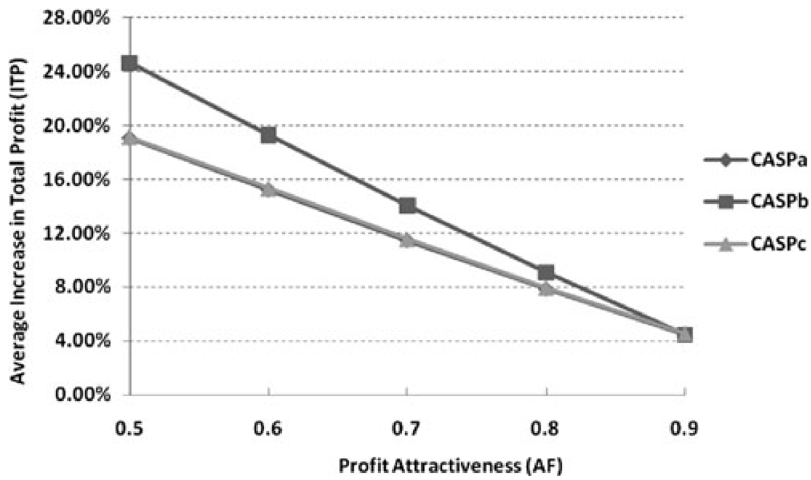
Figure 4: Simulation results for different AFs under the split lot policy.



FCFS_m are more significant in terms of total profit (TP) but less significant in terms of CU; and (ii) $CASP_b$ performs best among the three *CASP* models in almost every CT scenario except the case when CT $\geq$ 0.8 under the whole lot policy. In particular, when capacity is tight (smaller CT value), $CASP_b$ performs significantly better than $CASP_a$ and $CASP_c$.

Figures 4 and 5 show that: (i) When AF is smaller, corresponding to a larger difference in revenue among different classes of products, the improvement of the three *CASP* models over FCFS_m is more significant in terms of TP; and (ii) $CASP_b$ performs significantly better than $CASP_a$ and $CASP_c$ for almost every AF value except the case where AF = 0.9 under the whole lot policy. In particular, the

Figure 5: Simulation results for different AFs under the whole lot policy.



smaller the value of AF, the more significant is the advantage of $CASP_b$. Additional tables of our analysis can be obtained from the authors on request.

Comparison of CASP Heuristics and DCAP Model

Barut and Sridharan's (2005) benchmark DCAP model shows average TP improvements for the split lot policy and whole lot policy over the FCFS model of 6% and 8%, respectively. In comparison, the best performing CASP model is $CASP_b$ and it has the highest average ITP for the split lot policy and whole lot policy over FCFS of 15% and 14%, respectively (Figure 1). In Figure 6 , we show that for all relative profitability structures of DRP, SRP, and IRP, and using the split lot policy, all three *CASP* models outperform DCAP. $CASP_b$ performs best with an average of 8% improvement in TP over DCAP. In addition, we note that $CASP_b$ shows the biggest profit improvement over DCAP for the relative profitability structure of DRP and SRP. Likewise, in Figure 7, all three *CASP* heuristics also outperform DCAP for all relative profitability structures of DRP, SRP, and IRP, using the whole lot policy. The best performing model is $CASP_b$ with a 6% average TP improvement over DCAP. We also note that $CASP_b$ has the biggest profit improvement over DCAP for the relative profitability structure of DRP and SRP.

MANAGERIAL INSIGHTS

Our study should be interesting for managers because our experiment scenarios include a variety of demand and capacity environments. We simulate a total of 200 scenarios based on five levels of AF, five levels of CT, two levels of OSF, two levels of ORF, and two levels of CV. Although this environment is indicative of the fashion industry, our experimental settings can be adjusted to any industry environment.

Figure 6: Models of $CASP_{a-c}$ versus DCAP under the split lot policy.

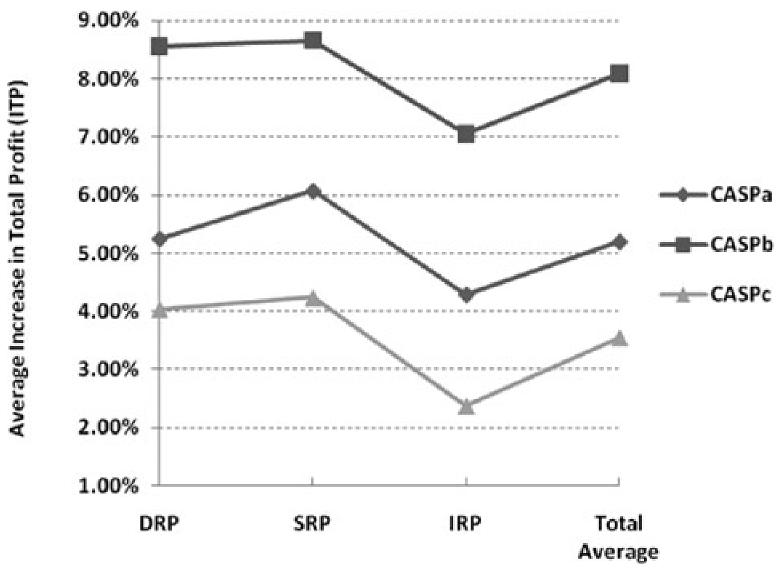
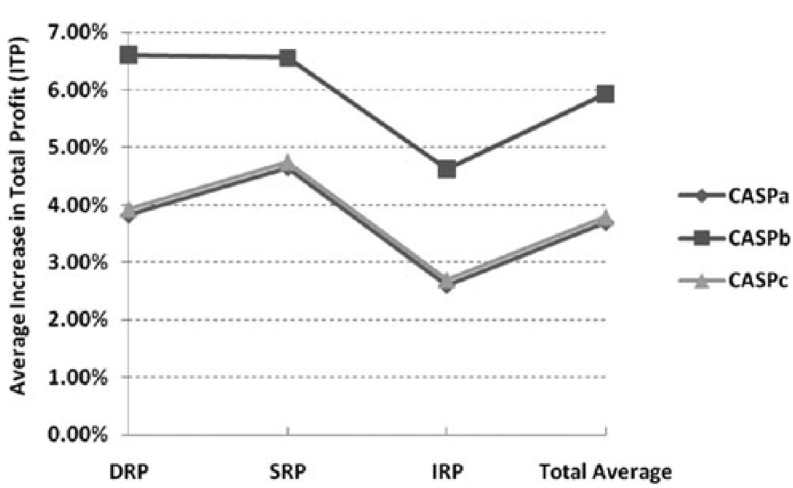


Figure 7: Models of $CASP_{a-c}$ versus DCAP under the whole lot policy.



We should point out the introduction of a switching point in the heuristic has provided significant improvement in performance of the CASP heuristics. The importance of a switching point can be traced back to solving the tradeoff between forward and backward allocation. With backward allocation, the early capacity is not utilized and thus may help the firm accept subsequent orders with earlier due dates; however, early capacity may be lost if not used. In contrast, with forward allocation, early capacity is more efficiently used. However, it may prevent the firm from accepting subsequent orders with earlier due dates. Thus the introduction of a switching point provides a better balance between forward and backward allocation resulting in improved utilization of available capacity.

In the dynamic fashion industry where companies face the problem of obsolete inventory, final specifications for the apparel related to style and colors are provided closer to the selling season although orders are placed months earlier to reserve capacity at the production facility. The CASP heuristics with the inclusion of a switching point only allocate production during the second half of the planning horizon so as to be closer to the delivery date. This is a desirable outcome because finishing early would incur inventory holding cost.

Although Barut and Sridharan (2005, p. 311) show that DCAP performed better than FCFS they also found a "weakness of DCAP—poor performance due to greediness—when product classes are not highly distinguishable and demand exceeds capacity only by a small amount." Our earlier analysis shows that $CASP_b$ outperforms DCAP using either the split lot or whole lot policy. We also find that using $CASP_b$ leads to an ITP without any loss in CU for a wide variety of operating conditions whether we use the split lot or whole lot policy. This kind of robustness can be explained by the improvement in CU/allocation capability of $CASP_b$ due to the incorporation of the switching point in the heuristic.

When capacity is tight (CT = 0.5) our analysis indicates that $CASP_b$ shows the highest profit improvement of approximately 25% over the FCFS model. This implies that the $CASP_b$ model does a better job allocating capacity compared to the FCFS policy when capacity is sufficient to meet only half the demand. Likewise, with a small AF ratio such as 0.5, which indicates a large price difference between the different product classes, $CASP_b$ shows an improvement in TP of 24% over the FCFS policy model. Our advice to managers is that under conditions of tight capacity and wide price differences between product classes, it is best to use $CASP_b$ to allocate capacity to obtain superior profit performance.

CONCLUSION AND FUTURE STUDY

This article investigates the capacity allocation and order acceptation problem in order-driven production systems. We develop three heuristics ($CASP_a$, $CASP_b$, and $CASP_c$) with a switching point to address this problem and evaluate the performance of the different heuristics over 200 scenarios. All three of the capacity allocations with switching point heuristics perform better than the FCFS, modified FCFS, and Barut and Sridharan's (2005) DCAP models. In particular, our best heuristic is $CASP_b$ and it is 15% and 8% better than the FCFS and DCAP models, respectively, under the split lot policy. Under the whole lot policy, $CASP_b$ outperforms the FCFS model and DCAP by 14% and 6%, respectively. The introduction of a switching point allows for a better balance between forward and backward allocation of available capacity and plays a significant role in improving TP.

Our heuristic not only simplifies the computation but also improves the performance compared with the existing models in the literature. The incorporation of the unique switching point logic in the CASP heuristics is the major reason for the improved performance. Therefore, managers, particularly from small- and medium-sized companies, in both the service and manufacturing industries will appreciate the heuristic because it produces higher profits especially under operating conditions of tight capacity and large price differences between product classes.

Our research is not without limitations. One limitation is demand reforecasting. Mukhopadhyay, Samaddar, and Colville's (2007) study indicates that airlines benefit from making forecasting adjustments. However, no study of order-driven production systems has provided any suggestions to handle reforecasting. Another limitation deals with the assumption of independence of order demand. Although this is true in most cases, there could be situations where demand is dependent. We have not seen any study in this area that deals with the assumption of dependent demand. As such, future research could address the reforecasting issue and relax the assumption of independent order demand. Although we have used a wide variety of operating conditions to improve generalizability of the results, we assume no cancellation of orders, tardiness, cost of finishing early, or multiple shipments. In addition, we have used three product classes in our experiments but extending the number of product classes will not impact the applicability of the heuristic. In general, it would be desirable to improve the model to derive a good solution for an operating environment that is usually more complex than is currently being tested.

Another potential area of research is to combine the heuristics we explore in this article with some advanced dynamic models, such as the DCAP model in Barut and Sridharan (2005) and the MRBCM model in Deng et al. (2008). We suspect that this combination will lead to further improvement in performance and a potential contribution for this area.

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