Setting Due Dates and Scheduling Jobs to Maximize Customer Satisfaction and Profits

Fall 2003

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ABSTRACT

Dynamic job shop scheduling research has previously assumed that the probability of the customer placing an order is always one, implying that customers will place orders regardless of lead times quoted from the producer and customer lead time expectations. As firms increasingly compete on the basis of the delivery speed and reputation, the relative performance of quoted versus actual realized lead times will have a strong effect on whether the customer will place future orders or not. Previous research has not considered differing customer requirements or the impact on the customer's subjective assessment of the overall purchase performance and subsequently on customer satisfaction and repurchases intentions. This paper formally integrates concepts from operations management, marketing, and consumer decision theory into a single due date scheduling framework in order to model the antecedents and consequences of customer satisfaction. We use the results on dynamic priority queues to propose the new way of quoting due dates by explicitly considering the customers lead time requirements. Simulation experiments reveal that job shop policies and machine capacities have significant impact on customer satisfaction and subsequently, on net profit. Finally, we show that dynamic due date quotation policy performs significantly better than several other policies previously tested in the literature.

Keywords: job shop scheduling, decision theory, consumer behavior, simulation

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1. Introduction

In contemporary manufacturing environments, firms compete on the basis of delivery speed and delivery reliability as well as with other competitive capabilities such as price, and quality. This is evident from the consistently high importance assigned to the speedy and on time delivery capabilities by the manufacturing managers in Europe, Japan, and the United states (Kim and Miller 1992). Global manufacturing managers increasingly understand the competitive necessity of addressing customer satisfaction during the planning and scheduling of manufacturing and service systems (Carmon and Shanthikumar 1995, Larsen 1987, and Lindley 1988). Similarly, empirical research findings from the marketing and accounting literature demonstrate the positive impact of customer satisfaction on repurchase intentions, retention rates, and profitability (Anderson and Sullivan 1993, Ittner and Larcker 1999, Reichheld 1996, and Bolton 1998). Moreover, the effect of customer satisfaction on firm performance varies according to industry characteristics, and is more significant in manufacturing and service industries than in retail businesses (Ittner and Larcker, 1999).

Previous research involving aspects of manufacturing production control has typically incorporated customer goodwill in tardiness costs so that late deliveries incur increased tardy costs that represent lost goodwill (reduced or lost future business). While capturing the rudiments of customer satisfaction, this construct obscures the drivers of customer satisfaction and fails to relate customer satisfaction to repeat business and market share. In this paper, we explicitly model customer satisfaction based on cumulative customer experience with a vendor, on the importance of a particular customer order, and on competitive industry lead time characteristics. Further, we model the result that customers update expectations when they acquire and process pertinent information regarding service quality. Customer satisfaction subsequently drives customer repurchase intentions and producer market share levels.

More specifically, we develop a practical job shop scheduling framework that models the relationships between due date quotation and dispatching policies, customer satisfaction, and net profit in an integrated manner. In order to model customer satisfaction in a scheduling and planning context, we formally integrate concepts from marketing, behavioral decision theory, and operations management into a single model. This model quantifies the antecedents and consequences of customer satisfaction and delivery speed in order to effectively analyze the impact of due date management policies and capacity decisions on the net profit. Our model incorporates the relationship between perceived service quality constructs taken from the customer satisfaction literature, and the product purchase constructs from the marketing literature to model these consequences of customer satisfaction. Thus, our model links local performance measures such as production lead times to strategic performance measures such as market share. Our methodology is quite flexible, general, and applicable in many production settings including both job shops and flow shops. The contributions of our research include:

1. Developing a generalized framework that models customer satisfaction and its consequences in a dynamic job shop scheduling context.

2. Investigating the impact of different due date management policies and shop capacities on customer satisfaction, market share, and net profit.

3. Studying the performance of the proposed due date assignment policy as compared to other policies previously proposed in literature.

The remainder of this paper is organized as follows. The next section reviews the previous research related to dynamic job shop scheduling. Section 3 describes our customer satisfaction scheduling model and its importance in detail. Section 4 discusses the role of dispatching rules and due date quotation policies in relation to our model. Section 5 outlines the experimental study to validate the model, while Section 6 provides the extensive analysis of the results of the study. Section 6 concludes with a summary of directions for further research.

2. Motivation and Literature Review

The importance of assigning and meeting the due dates in manufacturing is well recognized by both production managers and academic researchers. Due date quotation and job dispatching is particularly important in a dynamic production environment because of the random nature of the job arrivals, variable routing sequences, and processing characteristics, and so is widely studied in the literature. Most of this literature develops heuristic and analytic methods to select due dates that minimize holding costs and tardiness costs (or the proportion of tardy jobs) while attempting to quote a minimum possible lead time to an arriving order. Important work in due date assignment includes Eilon and Chowdhury (1976), Ragatz and Mabert (1984), Bertrand and Ooijen (2000), Enns (1995), Wein (1991), and Lawrence (1994, 1995). Complete reviews on due date research are available in the following papers (Cheng and Gupta 1989, Ragatz and Mabert 1984, Sen and Gupta 1984).

An implicit assumption in much of this research is that customers will place orders with certainty, no matter what lead time is quoted by the producer, what market expectations the customer has about "normal" lead times, or what previous experience the customer has had with the producer. As firms increasingly compete on the basis of the delivery speed and reputation, the relative performance of quoted and actual realized lead times will have a strong effect on whether the customer would place an order or not. Barman and Laforge (1998) have indirectly referred to this issue through their suggestion to relate the traditional research-based performance measures such as flow time and tardiness to the strategic objectives of the firm in order to for studies to have managerial significance. Related to our work, Webster (2002) developed a lead-time and pricing model for make-to-order firm that examined policies for adjusting price and capacity in response to periodic and unpredictable shifts in how the market prices and lead times, but did not explicitly model dynamic the impact of delivery reliability on the customer satisfaction and net profit as we do.

A high-impact strategic objective of many producer firms is customer satisfaction. Research suggests that higher customer satisfaction improves the long-run financial performance of a firm by reducing price elasticity and costs, while increasing repurchase intentions, improving retention rates, increasing profitability, and building loyalty among existing customers (e.g., Reichheld 1996, Bolton 1998, Anderson and Sullivan 1993, Anderson et al. 1994). A survey conducted by Ernst and Young (1991) supported these findings and have found that 54% of the organizations in 1988 and 80% in 1991 considered customer satisfaction as an important factor during strategic planning decisions, and predicted that these percentages would increase up to 96% by 1994. Further evidence of the growing recognition of customer satisfaction is manifested by empirical research in accounting as well, which has shown that customer satisfaction has a significant impact on various accounting related performance measures and stock market dynamics (Ittner and Larcker 1999).

Moodie (1999) reported that industry consumers evaluate the delivery service reputation of a potential vendor before sending it a request for quotation, where delivery service reputation depends upon the performance of the vendor compared to consumer expectations. In a manufacturing setting, customer evaluations are based on order characteristics, personal preferences, firm strategy and objectives, and on characteristics of the particular decision situation (Frank et al. 1972). Parasuraman et al. (1985) have related scheduling to service performance and customer satisfaction by studying the implications of gaps between expected and perceived levels of service. They evaluated different dimensions affecting service quality, of which two are directly related to scheduling performance: delivery reliability and service responsiveness. Barman and Laforge (1998) showed that delivery speed and delivery reliability, and hence customer satisfaction, are functions of due date quotation and dispatching policies. Inman et al. (1997) developed a general model of post-consumption evaluation using utility theory and consumer behavior theory to show how post consumption evaluation changes as customer expectations and needs evolve. In their model, a consumer's perception of overall service quality depends upon a comparison between customer expectations and actual service experienced, and so is contingent upon post-consumption customer evaluation. In a scheduling context, customers have differing expectations regarding order lead time quotations and delivery promises (Lawrence 1994, Weng 1998) depending upon the purpose and the priority of the order. For example, a critical order for an unexpected stock out situation would require a shorter lead time and superior delivery compared to a non-critical order for routine inventory replenishment (Lawrence 1994). These differing expectations will cause customer post-consumption evaluation of the producer to vary with the context of the order. In the following section, we present a due date model with customer satisfaction that captures the relationships between shop scheduling policies, customer satisfaction, and net profit of the firm in an integrated manner by including the behavioral characteristics of the business customer.

3. Due Date Model with Customer Satisfaction

Our framework for due date assignment, shop scheduling and customer satisfaction is shown in Figure 1. As shown in the figure, dispatching rules and due date quotation policies impact delivery reliability and delivery speed, and affect total profit due to tardy costs and inventory holding costs. Customer satisfaction is dependent on delivery reliability and delivery speed as moderated by customer expectations. Delivery speed and customer satisfaction drive market share which in turn impacts total profit, as do tardy costs and inventory holding costs. The novel aspect of our model is the use of customer expectation, customer satisfaction, and market share constructs, whereas most previous production scheduling research has focused on the top half of Figure 1, which assumes that profits are dependent on costs alone. We mathematically define our model in the sections below.

3.1 Customer Satisfaction Model

Because customers usually estimate their future preferences based on current preferences, customer decisions about continuing a relationship with a supplier are based on cumulative customer satisfaction with the supplier (Bolton 1998). Customers continuously update their beliefs about the future value of their relationship with the supplier based on their recent experiences. This updating process occurs using an anchoring and adjustment heuristic, in which customers anchor their satisfaction based on the cumulative previous satisfaction level and then adjust it by the current satisfaction experience (Hogarth and Einhorn 1992, Bolton 1998). Customers garner this information about service quality during encounters which take place during commercial exchanges. In a scheduling context, customers learn about the lead time (delivery speed) promises of a firm from its order quotations, and about its delivery reliability form its order fulfillment. Customers can then compare current service quality with their prior cumulative assessment to form a new assessment of the value of future service (Bolton 1998). We therefore model cumulative satisfaction Φ_i after transaction i as a convex combination of current satisfaction and cumulative historical satisfaction:

$$\Phi_i = \alpha\varphi_i + (1-\alpha)\Phi_{i-1} \tag{1}$$

where ϕ_i is the satisfaction received from the post-consumption evaluation of order transaction i, Φ_{i-1} is the cumulative satisfaction level prior to the transaction, and α is a weighting or smoothing parameter. The most common assumption in the customer satisfaction literature is that producer performance has a linear effect on satisfaction (Anderson 1994, Bell 1985). We also assume the linear effects in our satisfaction model. A transaction can be either a completed and successful purchase transaction, or it can be a lost purchase transaction. In the language of consumer psychology, cumulative satisfaction Φi provides an *anchor* for consumer satisfaction while transaction satisfaction ϕi updates or *adjusts* long-term satisfaction. Factor α ($0 \leq \alpha \leq 1$) is a parameter that attributes relative weights to anchoring and adjustment processes. These weights depend upon the value of the customer relationship with the manufacturer. A highly satisfied and long-time customer is less likely to drastically change her perception about a manufacturer after a bad consumption experience compared to a new customer or a customer with poor long-term satisfaction. Thus, our model would provide the manufacturer with the flexibility needed to incorporate different kinds of relationships she has with her customers.

Customer satisfaction has been studied by researchers from various perspectives. For example, customer satisfaction has been defined as an outcome of expectancy-disconfirmation evaluation (Oliver 1980). Giese and Cote (2000) have provided an excellent review on customer satisfaction. Our estimation of Φ_t is motivated by this research that finds customer satisfaction to be contingent upon two factors: (1) overall satisfaction a customer receives from the service, (2) the extent to which the service either fails or exceeds expectations (Ittner and Larcker 1999, Anderson and Sullivan 1993, Bolton 1998, and Inman, Dyer and Jia 1997, and Thaler 1985).

We are interested in modeling customer satisfaction from a scheduling perspective. It was previously noted that delivery speed and reliability have been identified as the main indicators of the scheduling performance. We thus model customer satisfaction from a delivery speed and delivery reliability perspective. Delivery speed can be defined as a comparison of the expected lead time by the customer and the lead time quoted by the manufacturer. We expect that delivery speed is context specific and depends upon customer expectations. For example, if a manufacturer quotes a fixed lead time of 3 weeks and if a customer expects order delivery within 4 weeks, then delivery speed is construed as positive; however if customer expects order delivery within 2 weeks, then the quoted delivery speed is construed as negative. Delivery reliability measures the performance of actual lead times with respect to the quoted lead times. We model acquisition utility is a function of a perceived performance of an order on delivery speed and delivery reliability dimensions:

$$U_{ij}^{A} = \omega_1 \left(L_{ij}^{E} - L_{ij}^{Q}\right)^{+} + \omega_2 \left(L_{ij}^{E} - L_{ij}^{Q}\right)^{-} + \eta_1 \left(L_{ij}^{Q} - L_{ij}^{A}\right)^{+} + \eta_2 \left(L_{ij}^{Q} - L_{ij}^{A}\right)^{-} + U_{ij}^{E} \qquad (2)$$

where, U^{E}_{ij} = Expected utility for customer *i* from order *j*

U^{A}_{ij} = Acquisition utility to customer *i* from order *j*

L^{E}_{ij} = Expected lead time of customer *i* for order *j*

L^{Q}_{ij} = Lead time quoted by manufacturer for order *ij*

L^{A}_{ij} = Actual lead time on the shop floor for order *ij*

Parameters ω_1, ω_2, η_1, and η_2 scale the customer utility gained (lost) when lead time expectations are exceeded (disappointed). Disappointment is a psychological reaction to a choice outcome that doesn't meet one's expectations (Bell 1985). The first term in equation (2) represents the satisfaction received by a customer due to elation when manufacturer quotes a lead time shorter than her expectations. Second and fourth terms model dissatisfaction for a customer if manufacturer doesn't meet expectations on delivery speed and reliability fronts respectively. The third term indicates satisfaction received by a customer when a manufacturer completes an order earlier than its due date. Expected utility U^{E}_{ij} is the utility a customer gains when a manufacturer quotes a lead time that is equal to her expected lead time and then dispatches the order exactly on its due date. Note that if expected, quoted, and actual lead times are identical (e.g., $L^{E}_{ij} = L^{Q}_{ij} = L^{A}_{ij}$), then acquisition utility is identical to expected utility ($U^{A}_{ij} = U^{E}_{ij}$), where acquisition utility is the net utility experienced by a customer from a transaction.

Customers may not desire early delivery of an order prior to its due date, but will generally be more unhappy if the producer completes the order after its due date. This argument is well supported by the axioms of prospect theory which postulates that people evaluate outcomes on the basis of potential gains or losses perceived with respect to a reference point rather than absolute values and weigh losses much more heavily than gains when making decisions (Kahneman and Tversky 1979). Consistent with this theory, empirical studies have also found that disappointment has a larger impact on post choice valuation than elation (e.g., Anderson and Sullivan 1993). This asymmetrical effect can be included in our model by setting values of

$$\omega_2 \geq \omega_1 \ \textit{and} \ \eta_2 \geq \eta_1 .$$

If perceived performance exceeds (falls short of) expected performance, then satisfaction is a function of the direct impact perceived performance plus a gain (loss) in satisfaction from an unexpected surprise of finding performance to be greater (less) than expectations. We model transaction utility U^{T}_{ij} as the difference between acquisition utility U^{A}_{ij} and expected utility U^{E}_{ij}":

$$U_{ij}^{T} = U_{ij}^{A} - U_{ij}^{E} \qquad (3)$$

Then total or combined probability is defined as:

$$U_{ij}^{C} = U_{ij}^{A} + U_{ij}^{T} \tag{4}$$

The probability of a customer placing an order is a decreasing function of the difference between quoted and expected lead time. If a manufacturer quotes a long lead time, the customer might cancel the offered quotation. However, because manufacturer was not able to meet customer's expectations about the lead time and delivery, the customer would experience disappointment after canceling the quotation. This dissatisfaction phenomenon is similar to Giese and Cote (2000) definitions of the customer dissatisfaction, which would be incurred even without the purchase transaction. And this can be modeled in the following manner: In such situations, $U^{A}_{ij} = 0$ because of no consumption of the order; However, $U^{T}_{ij} = 0 - U^{E}_{ij}$ because a manufacturer is not able to meet customer's expectations about the lead time, which implies that:

$$\Phi_{ij} = -U^{E}_{ij} \tag{5}$$

3.2 Market Share and Profit Model

Prior empirical research has provided evidence for the premise that market share and total revenue of a firm increase with customer satisfaction. If a manufacturer has a high service reputation and quotes a competitive lead time, then she has higher chances of winning an order. Given this support, we can reasonably assume that probability of receiving an order quotation is a function of a reputation of a firm (Moodie 1999) and probability of winning an order is a function of both delivery speed (Duenyas 1995), and reputation. However, studies have found that relationship between customer repurchase intentions and customer satisfaction is relatively constant over some part of customer satisfaction and changes only after satisfaction moves thorough various threshold levels (Ittner and Larcker 1999). We first model the probability of the firm being asked to provide a quotation for an order O as an S-shaped function:

$$\mathrm{P}(O_{ij} = 1|S_{ij}) = \frac{1}{\left(1 + \exp(aS_{ij} + b)\right)} \tag{6}$$

where $O_{ij} \in \{0, 1\}$ and satisfaction index $S_{ij} = \Phi_{ij} / 100$ is the normalized value of satisfaction. Hill (1989) has identified both delivery speed and customer satisfaction as the order winning criteria in the manufacturing environment. We model the probability of winning an order $O_{ij} \in \{0, 1\}$ as a function of both delivery reliability and customer satisfaction:

$$P\left(O_{ij}\right) = \delta_1 \left(L^{E}_{ij} - L^{Q}_{ij}\right) + \delta_2 (S_{ij}) \tag{7}$$

The weights δ_1 and δ_2 placed on these criteria depend upon specific characteristics of the particular customer and industry. We define the total profit of the firm as:

$$\Pi = \sum_i \sum_j \left(R_{ij} - C_{ij} - H_{ij} - E_{ij} - T_{ij} \right) \qquad (8)$$

where R_{ij} is the revenue from job j of customer i, C_{ij} is its cost of production, H_{ij} is its holding cost, Eij its early completion cost, and Tij its tardiness cost. Holding costs H are those costs associated with order flow time that capture the expenses associated with holding, storing, and handling inventory. Due date deviation (earliness and tardiness) costs represent costs incurred due to the failure to meet due dates exactly. Tardiness costs may represent tardiness penalty charges and delivery charges while earliness costs represent cost of holding finished goods if early shipments are prohibited. Tardiness T_{ij} or earliness E_{ij} of an order depends upon its due date D_{ij} and its completion time C_{ij}:

$$T_{ij} = \begin{cases} 0 & C_{ij} \le D_{ij} \\ \tau\left(C_{ij} - D_{ij}\right) & C_{ij} > D_{ij} \end{cases} \qquad (9)$$

$$E_{ij} = \begin{cases} \varepsilon\left(D_{ij} - C_{ij}\right) & C_{ij} \le D_{ij} \\ 0 & C_{ij} > D_{ij} \end{cases} \qquad (10)$$

where τ is the tardiness cost per time unit and ε is the unit earliness cost for jobs that complete before their due dates.

3.3 Role of Due Date Quotation and Dispatching Policies

Due date quotation polices affect the delivery speed because of their ability to control the lead time quoted to the customer. Similarly, dispatching policy affect the delivery reliability because of their ability to control the actual lead time of the order, so these operational policies indirectly control customer satisfaction and net profit. We investigated several well-known, widely-used, and widely-tested quotation policies in our study as described below.

3.3.1 M/M/1 Due Date Quotation (FDD)

M/M/1 due date quotation (FDD) uses basic queuing theory results assuming Poisson arrivals and exponential processing times, FCFS dispatching, and does not consider the priority of the customer. This policy is also called as Total work content based due date quotation policy. The expected lead time for job ij at machine m is thus estimated as the expected waiting time in an M/M/1 queuing system (Wagner

1975):

$$L_{ijm}^{A} = \frac{\rho_m}{(\mu_m - \lambda_m)} + \frac{1}{\mu_m} \tag{11}$$

3.3.2 Strict Priority Due Date Quotation (PDD)

Wein (1991) studied the non-preemptive priority queues by numerically estimating conditional sojourn time tail probabilities. Unfortunately, strict priority-based due date quotation is often not suited for practical applications. In such settings, even at moderate utilization levels the lead-times quoted to low priority customers are tremendously long (Kleinrock and Finkelstein 1967). Such due date quotation polices are favorable for high priority customers, but penalize low priority customers with long lead times. We implement the PDD policy here as:

$$L_{ijn(k)}^{A} = W_o \left\{ \left(1 - \sum_{k=p}^{k=P} \rho_k\right)\left(1 - \sum_{k=p+1}^{k=P} \rho_k\right) \right\}^{-1} + \frac{1}{\mu_i} \tag{12}$$

3.3.3 Dynamic Priority Due Date Quotation (DDD)

A First Come First Serve (FCFS) policy assumes that all orders have the same priority and so treats all jobs equally. In contrast, a strict priority discipline policy does not consider the impact on lower priority jobs when making lead time decisions. A compromise lead time policy might favor high priority customers, but would incorporate the time spent by low priority customers in the system. Kleinrock and Finkelstein (1967) studied dynamic priority dispatch policies where both job priority and time-in-queue are considered. These policies are quite flexible and by varying policy parameters, can model a range of policies varying from a strict priority policy to a pure first-come first-serve policy. Lead time $L_{ijm(p)}$ for order *ij* at machine *m* of priority type *p* is given by:

$$L_{ijm(p)} = \frac{\left[\dfrac{W_0}{(1-\rho_m)}\right] - \sum_{k=1}^{p-1} \rho_k W_k \left[1 - \left(\dfrac{b_k}{b_p}\right)^{\frac{1}{r}}\right]}{\left\{1 - \sum_{k=p+1}^{P} \rho_k \left[1 - \left(\dfrac{b_P}{b_k}\right)^{\frac{1}{r}}\right]\right\}} + \frac{1}{\mu_{m_j}} \tag{13}$$

where b_k is the weight for an order of priority type k, $b_p \geq b_k$ is the maximum weight assigned to any priority class, W_k the waiting time for order of priority type k; ρ_k is the portion of total machine utilization accountable by priority type k, the steady state machine utilization for machine m is ρ_m , and $0 \leq r \leq \infty$ is a parameter denotes the importance assigned to the time spent in the system by customers. Note that for the highest priority jobs, $b_k = b_p$ and lead time reduces to that of an M/M/1 queue comprised only of the highest priority jobs. Also note that as parameter r approaches ∞, the summation terms in the numerator and denominator diminish to zero and lead times approach those of a pure FCFS system. Similarly, as the parameter r approaches 0, lead times approach those of a strict priority system. This parameter adjustment allows us to quote lead-times in more flexible way. This is particularly useful when we optimize the quoted lead-times according to the dispatching policy and customer requirements. Table 7 shows how the parameter r varies as a function of dispatching policies for the DDD quotation policy.

Let N be the total number of operations to be performed on order j from customer i, then due date D_{ij} for job ij can be calculated as:

$$D_{ij} = f_{ij} + \sum_{n=1}^{N} L_{ijn(k)}^{A} \tag{14}$$

where f_{ij} is the fixed processing time of order ij and $L^{A}_{ijn(\mathrm{k})}$ is the lead-time of order ij of priority class k performed at operation n.

3.4 Dispatch Policies

We examined four dispatching rules common in the literature. Two were due date dependent rules: Earliest Due Date (EDD) and Operation Due Date (ODD); and two were due date independent rules: First Come First Serve (FCFS) and Order Priority (PRI). EDD rule dispatches the according to the final due date of the order. ODD rule dispatches jobs according to the due date of the immediate operation. FCFS dispatches jobs in order of arrival to a particular operation, and the PRI rule dispatches jobs according to the priority of the order. These dispatching rules were chosen to compare the impact of due date dependent rules versus due date independent rules on the shop performance.

4. Experimental Design

A simulation experiment was undertaken to investigate how different combinations of due date assignment and dispatching rules affected shop performance at different shop loads, and particularly to study the performance of dynamic due date setting policy compared to the other quotation policies used in the literature. The experimental design was full factorial with three factors: due date quotation policy (DDQP), dispatching policy (DP), and shop load ρ. These factors were tested at three, four and two levels respectively. The three due date rules were M/M/1 Due Date Quotation (FDD), Strict Priority Due Date Quotation (PDD), and Dynamic Priority Due Date Quotation (DDD) as described in the previous section. Shop utilization ρ was tested at medium and high loads to investigate the impact of the capacity on performance measures. The dispatching policy was tasted at 4 levels: EDD, ODD, PRI, and FCFS.

Testing each factor combination resulted in total of 3×4×2=24 experiments. Nine independent replications of 1,500 jobs were run for each factor combination. Six performance measures were captured for each experiment: net profit, customer satisfaction, tardiness costs, proportion of orders lost due to reputation and due to delivery speed, total costs, and quoted lead time. We were also interested in observing the behavior of satisfaction and net profit over time before the shop reached the conditions representative of a steady state, and so divided each replication of 1,500 jobs into 15 batches of 100 jobs each, and recorded the performance for each batch in succession.

The experimental setting was a job shop consisting of four machines with exponentially distributed processing times $\mu = 0.4$/week. The two machine utilization levels tested were $\rho = 75\%$ and $\rho = 65\%$. Other parameters used in all experiments were summarized in Table 1. We assumed that the each machine had the same expected utilization. The orders arrived to the shop according to Poisson distribution with arrival rate $\lambda = 0.3$/ week for the 75% shop utilization. Because the customers have different lead time expectations from a manufacturer, we modeled customers' lead time expectations using a uniform distribution on the interval of (3, 10) weeks. We assigned an arriving order to one of the three customer segments depending upon the lead time requested by the customer: High Priority (3 to 5.25 weeks), Medium Priority (5.25 to 7.75 weeks), and Low Priority (7.75 to 10 weeks). The mean number of operations (NOP) to be performed on an order was set to be four, but NOP was allowed to vary between 2 and 6 jobs to model work content variability. A routing plan was assigned to an order upon its arrival to the shop according to a pure job shop routing matrix. The price of an arriving order was set to \$100 and total costs for the order were set to \$75, of which \$60 were materials costs. Tardiness and inventory holding costs were excluded from the total cost in order to better estimate their impact on total profit. Marginal tardiness costs τ were set to 0.5% of the price of an order per day; and marginal inventory holding costs ε were set to 0.04% per day (or about 15% per year). Customer satisfaction parameter α was set to 0.5 and initial satisfaction index Φ_i was set to 80%.

Because the utility from the order would vary as per the order and situation characteristics, the uniform distribution was used to model ω_1, ω_2, η_1, and η_2 parameters. Finally, we did not consider the negotiation between the players in order to analyze the exact impact of the DDQP on the performance. This fixed set of these parameter values was used throughout the experiment to safeguard the study against confounds arising from the interactions between these parameters.

Finally, for the dynamic due date quotation policy (DDD), we exploited its adaptive nature by finding the best values for parameter *r* for each DDD experiment. Initial pilot experiments varied the value of DDD parameter *r* for different dispatch policies. Table 7 summarizes the values of parameter *r* that maximized profits for each DDD-priority rule combination and that were used in the main experiment. Note that *r* was lowest for PRI dispatching and highest for FCFS dispatching policy, consistent with the structure of DDD as discussed in Section 3.3.3.

5. Experimental Results

We examined the main effects of due date quotation policy (DDQP), dispatch policy (DP), and shop capacity (ρ) on the net profit using a three way ANOVA. The overall model was significant (Table 4) and revealed that shop capacity, DDQP, and DP had significant impact on the net profit. Following this overall result, we next examined the impact of tactical DDQP and DP policies.

We first tested the main effects of the DDQP, and the DP, and the interaction effect of the DDQP and the DP on the net profit in a two-way ANOVA. Principal results are reported in Tables 2 and 3 for shop utilization of $\rho = 75\%$. Results for medium utilization levels of $\rho = 65\ \%$ were similar, but are not reported here for parsimony. The overall model was significant, revealing significant main effects for both DDQP and DP on the net profit (Tables 4 and 5), suggesting that the net profit is dependent upon the due date quotation and dispatching policies for the given capacity level. Enns (1995) showed how due date quotation and dispatching policies affect the net profit through the scheduling costs. Our results support these findings. Moreover, our results also consider the impact of customer satisfaction and market share on the net profit along with the scheduling costs. In the following subsections, we discuss the impact of shop policies on satisfaction and net profit.

5.1 Impact of Dispatching Policy

We next tested the main effect of dispatch policies DP on the net profit for a given due date quotation policies DDQP. This analysis revealed that DP has a significant impact on net profit for due date quotation policies DDD and FDD (Tables 5 and 6). We subsequently used a contrast codes procedure to find the best combinations of DP for a given DDQP, which reveal that the FCFS dispatch policy resulted in significantly lower profits on average with the DDD quotation policy compared to EDD and ODD.

This finding can be explained using results from consumer behavior theory in the following way. If a firm uses a dynamic priority DDD quotation policy, then the customer initially is rewarded with positive utility because the firm quotes competitive lead-times and wins the order with an optimistic delivery promise. The customer, of course, expects due-date commitments to be met. Though the FCFS policy is very simple to implement, it ignores this commitment and treats all jobs as equal and prioritizes their dispatch based solely on their arrival times. This results in consistent failure to meet delivery promises for high and medium priority customers so that post-consumption customer evaluation is negative despite better pre-consumption evaluation and better initial order acceptance. Because of the asymmetric evaluation of the losses and gains from a purchase transaction, the negative utility of delivery disappointment more than offsets initial elation utility derived from an early due date promise. Net negative utility damages firm reputation and degrades customer retention probabilities. The outcome of these phenomena are evident in Table 3, where profits and customer satisfaction for DDD/FCFS are high for low priority customers and lower for medium and high priority customers.

In contrast, the EDD and ODD dispatching policies prioritize jobs based on the due date commitments made by the firm and work to link shop activities to marketing promises. Post-consumption utility is greater for high and medium priority orders using DDD/EDD and DDD/ODD policies and so the customer is more likely to place repeat orders in the future. Table 3 shows how customer satisfaction and profits improve markedly for medium and high priority orders relative to low priority orders when DDD/EDD and DDD/ODD policies are employed.

Similar results were obtained for FDD and PDD due date quotation policies used in conjunction with FCFS, EDD, and ODD dispatch polices. These findings clearly suggested the importance of using due date related dispatch policies to improve customer satisfaction by improving delivery reliability performance.

The strict priority PRI dispatching policy coupled with the DDD due date quotation policy was able to accelerate high and medium priority orders through the shop at the expense of the low priority orders, and so generated high satisfaction for the high and medium priority segments. However, since PRI always delays low priority jobs in favor of high priority work, it consistently failed to meet the requirements of low priority orders and thus generated higher dissatisfaction for low priority orders (Table 3).

These results show that alternative dispatch policies have the ability to satisfy different customer segments to different degrees and suggest that long term success in a particular segment demands an appropriate customer-driven response. The firm must understand the delivery needs of potential customers and develop dispatching strategies to meet those needs. Selection of an appropriate dispatch policy increases customer satisfaction, grows market share, and ultimately improves profits.

5.2 Impact of Due Date Quotation Policy

We tested the effect of due date quotation policy DDQP and dispatch policy DP on average lead time in a two-way ANOVA and found that both the main effects and the interaction effects were statistically insignificant (Table 6). Although mean lead times were almost the same for all DDQP, DDQP *does* have a statistically significant impact on other performance measures such as net profit and customer satisfaction (Table 5). This outcome can be explained in the following manner. Firms must consider the needs of customers, the characteristics of a particular order, and general market characteristics when making delivery promise decisions. For example, Lawrence (1994) identified four market segments for orders in a job shop scheduling context. By setting due dates in accordance with the needs of customers and the demands of particular orders, overall customer utility increases, satisfaction increases, and profits increase (Table 3).

Specifically, due date quotation policies FDD and PDD resulted in lower customer satisfaction and reduced profits compared to the DDD due date policy (Table 3). FDD does not adequately differentiate between customer segments and develops lead time quotations based on total work content without regard to the priority of an order. Similarly, PDD incurred higher dissatisfaction for the low priority orders because it quoted considerably longer lead times for low priority orders. However, it unnecessarily exceeded the requirements of high priority orders and earned high satisfaction scores for corresponding customers when used with an appropriate dispatching policy. Note that FDD and PDD are each highly competitive one of the three segments (low priority and high priority, respectively), but are in inferior for the correspondingly opposite segment (high priority and low priority, respectively).

In contrast to FDD and PDD, the DDD due date policy quoted lead times that better balanced customer needs and order requirements with shop operating characteristics, and thus generated higher customer satisfaction and net profits across all customer priority segments. Though DDD did not dominate every priority segment, its aggregate performance was better than the either FDD or PDD. For example, PDD generated the highest profits for high end customers, but the lowest profits for low end customers. FDD generated the lowest profits for high end customers and the highest profits for low end customers. In contrast, DDD generated good profits across all groups and the highest aggregate profits of the three due date policies. Customer satisfaction and market share are plotted in Figures 2 and 3 for different due date dispatching policies. These figures show that over time, the DDD due date policy comes to dominate FDD and PDD policies as its better delivery performance drives up customer satisfaction and consequently, market share. This result demonstrates the importance of adequately incorporating consumer decision theory and customer satisfaction concepts into shop scheduling decisions.

5.3 Sensitivity Analysis

An important reason why DDD quotation policy performs better than FDD and PDD is because it adapts to changing customer expectations over time. The rate of adaptation is determined by parameter *r* shown in equation (13) which was set to the values shown in Table 7 for the main experiment. To test the sensitivity of our results to this parameter, we varied *r* from 0 to 1. Figure shows that customer satisfaction and net profits are quite sensitive to *r* with satisfaction and profits maximized at $r \cong 0.75$. As parameter *r* approaches 1, the DDD policy approaches FDD and aggregate performance deteriorates. As *r* approaches 0, DDD approaches PDD and performance again deteriorates. This result indicates the importance of balancing both shop characteristics and customer requirements to achieve the best possible outcome.

Since investment in the shop capacity is a strategic decision that has the capability to affect the shop performance (Ragatz and Mabert 1984), we investigated the impact of the different shop capacities on net profit for selected combinations of DDQP and DP. Figure 5 shows that at higher shop loads, net profit deteriorated significantly because shop congestion increased lead times, increased lead time uncertainty, and decreased delivery reliability. Conversely, lower shop loads resulted in shorter lead times, less uncertainty, increased delivery reliability, and higher profits. This result again indicates the necessity of linking shop performance characteristics with the needs of customers and the marketplace.

6. Conclusions and Future Scope

In this paper we have demonstrated an important three-way linkage between production control policies, marketing outcomes, and overall firm performance. By proper selection of production control policies such as due date quotation and dispatch policies, marketing outcomes such as customer satisfaction and repeat purchase are improved, and aggregate firm performance measures such as market share and profitability are benefited.

Our experiments show that due date quotation and dispatch policies can have a significant impact on customer satisfaction and consequently, on net profit. Alternate production control policies satisfy different customer segments to different degrees. For example, the combination of PDD due date quotation and PRI dispatching provided high levels of customer satisfaction for high priority customers, but at the expense of the satisfaction of low priority customers. In contrast, FDD due date quotation and FCFS dispatch provided high levels of satisfaction for low priority customers but at the expense of high priority customers. The most profitable policy, DDD due date quotation with EDD dispatch, provided good levels of satisfaction for all customer priority classes, but did not dominate any. By better understanding these trade-offs, firms can better serve their customers, ensure better repeat business, and ultimately, improve profitability.

Our research suggests several opportunities for follow-on work. First, customers are willing to pay a higher price for shorter lead times in many high priority production situations (Moodie 1999). In such situations, the main problem is to trade-off extra profit margins with a higher risk of incurring tardiness penalties. Further research is needed in which different profit margins are assigned to different customer segments and the impact on customer satisfaction and total profits investigated.

A wide variety of due date quotation and dispatching policies have been proposed in the literature. While we believe that the policies tested in this paper serve to span the set of policies, further testing might reveal additional insights into the performance of alternative policies on customer performance.

Finally, we have assumed fixed capacity in this paper. Hence, the production facility was not able to improve its performance above a certain level due to capacity constraints. The theory of constraints aims to identify such throughput obstacles and mitigate them to enhance system performance. In many practical settings, it is possible to create "excess capacity" in the shop by either planning overtime at tactical level or investing in machines at strategic level. Another obvious extension of our model would be to include these capacity decisions at more detailed level and to study their impact on overall profitability.

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ELT (in weeks)	**Utility function parameters**	**Priority weights**
Uniform (3, 10)	$\omega_1, \eta_1 = Uniform(0,5)$ $\omega_2, \eta_2 = Uniform(5,10)$	Ratio = $\frac{b_i}{b_{i+1}}$ = 0.5

Table 1: Description of parameters used in all simulation experiments.

Due date quotation and dispatching policies	**Net Profit**	**Mean Sat Index (Initial =80)**	**Proportion of orders lost due to delivery speed**	**Proportion of orders lost due to dissatisfaction**	**Total Scheduling related costs**	**Quoted Lead Time**
DDD and EDD	27349	91.9	8.46	10.1	3941	47.4
DDD and ODD	27010	88.2	8.66	11	3930	47.7
DDD and PRI	26336	87.3	8.5	13.6	4029	44.3
DDD and FCFS	25694	83	8	15.6	4233	47.0
FDD and EDD	26274	89.9	13.5	10.2	3071	46.8
FDD and FCFS	25137	80.2	12.9	14.5	3315	46.8
FDD and ODD	26273	89.5	13.5	10.2	3075	46.8
FDD and PRI	25225	81.8	13.2	14	3241	46.8
PDD and EDD	23552	70.5	5.8	28	3641	42.6
PDD and FCFS	22799	66.25	5.5	31	3690	44.7
PDD and PRI	23244	68.1	6	29.4	3567	47.9
PDD and ODD	23403	68.6	5.4	29.2	3589	48.9

Table 2: Performance of shop on different dimensions at 75 % shop load

DDQP/DP Combinations	Total Tardiness Cost HP	MP	LP	Net Profit HP	MP	LP	Satisfaction / order HP	MP	LP
DDD and EDD	336	329	189	7562	9998	9789	4.9	6.5	20.3
DDD and ODD	344	318	143	7381	9789	9840	4.86	6	21.1
DDD and PRI	283	283	324	7625	9906	8797	5.06	7.1	16.4
DDD and FCFS	453	377	168	6377	9716	9590	-6.95	4.6	20.1
FDD and EDD	126	198	208	6321	9977	9974	-14.3	5.7	32
FDD and ODD	126	198.2	208.2	6081	9678	9574	-13.9	5.4	30.8
FDD and PRI	60	182	356	6665	9854	9354	-11.2	6.3	28
FDD and FCFS	149	234	253	5915	9917	9614	-14.9	5.46	31.5
PDD and EDD	551	301.6	2.2	7879	9320	6355	5.55	17.14	-24
PDD and ODD	561	276	25.5	7882	9136	6399	5.82	16.4	-23.8
PDD and PRI	512	279	64	7986	9064	6198	6.31	14.32	-28.7
PDD and FCFS	618	294	3.92	7498	8990	6286	-4.82	15.4	-24.5

Table 3: Performance of DDQP and DP for high (HP), medium (MP), and low (LP) priority jobs

Source	DF	SSE	MSE	F Value	Pr>F
Model	6	584,880,754	97,480,126	50.75	< 0.0001
DDQP	2	100,471,336	50,235,668	26.15	< 0.0001
DP	3	16,110,242	5,370,081	2.8	0.0412
Shop Capacity	6	468,299,176	468,299,176	243.81	< 0.0001
Error	209	401,431,591	1,920,725		
Total	215	986,312,345			

Table 4: Three Way ANOVA – Net Profit by Shop Capacity, DP, and DDQP

Source	DF	SSE	MSE	F Value	Pr>F
Model	11	245468384.4	22315307.7	13.65	< 0.0001
DDQP	2	217262320.3	108631160.1	66.46	< 0.0001
DP	3	24506180.8	8168726.9	5.00	< 0.0029
DDQP*DP	6	3699883.3	616647.2	0.38	0.8919
Error	96	156920631.8			
Total	107	402389016.2			

Table 5: Two Way ANOVA – Net Profit by DP and DDQP

Source	DF	SSE	MSE	F Value	Pr>F
Model	11	48.72105	4.42918	0.35	0.9710
DDQP	2	25.45102	12.72551	1.01	0.3684
DP	3	12.27189	4.09063	0.32	0.8078
DDQP*DP	6	10.99812	1.83302	0.15	0.9896
Error	96	1210.853886	12.61306		
Total	107	1259.574919			

Table 6: Two Way ANOVA – Mean Lead Time by DP and DDQP

No.	Dynamic due date quotation and dispatching policy combination	Parameter *r*
1	DDD and EDD	0.75
2	DDD and ODD	0.8
3	DDD and PRI	0.45
4	DDD and FCFS	1.4

Table 7: Parameter *r* used with dispatch policy and due date quotation policy combinations

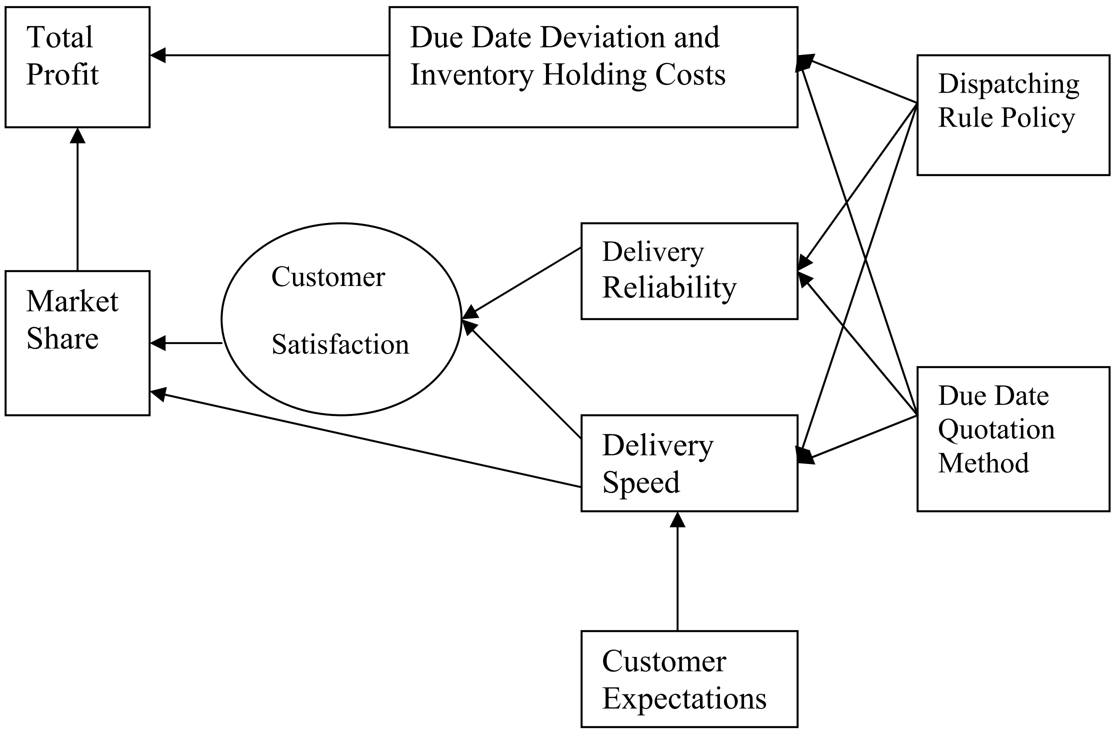

Figure 1: Framework for dynamic job shop scheduling

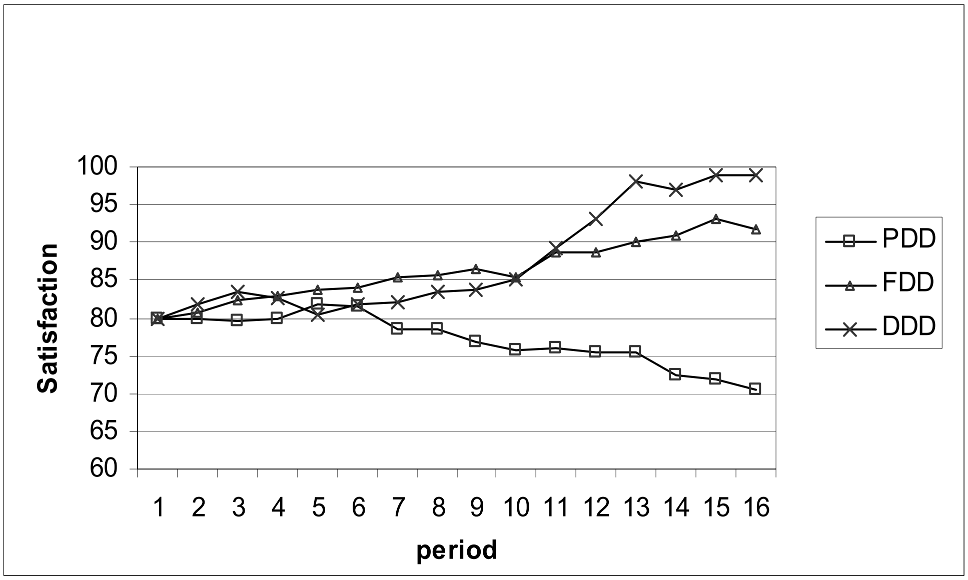

Figure 2: Effect of due date quotation policies on customer satisfaction at 75% shop load.

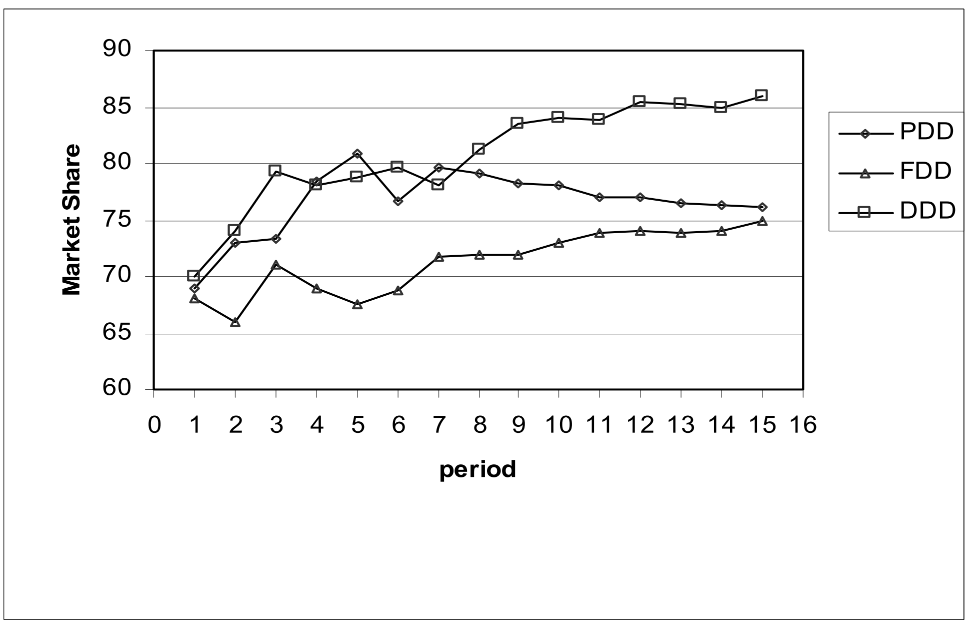

Figure 3: Effect of DDQP on market share for EDD dispatching and 75% shop load

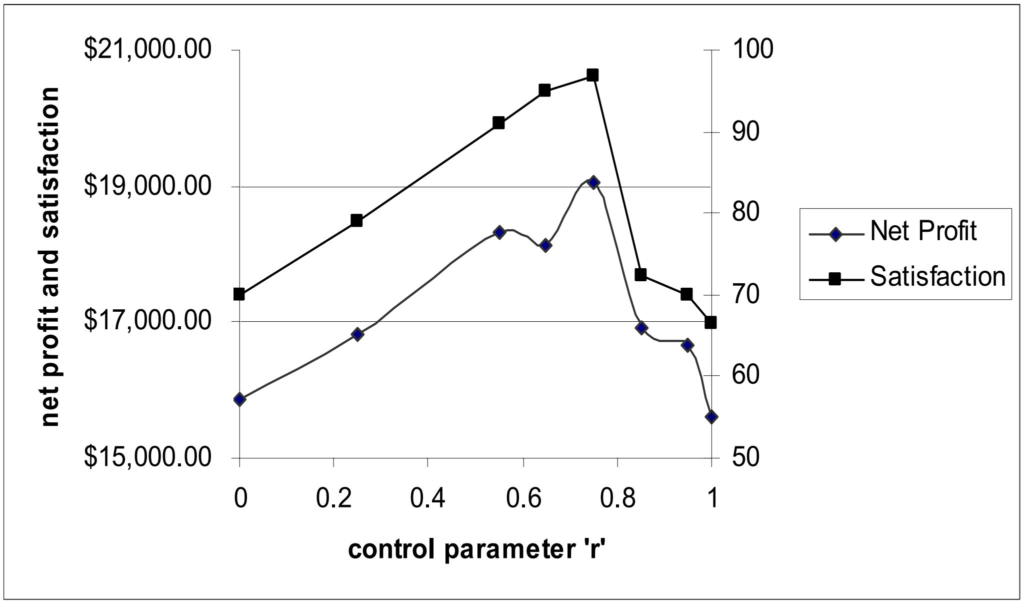

Figure 4: Effect of controlling parameter *r* for the PDD due date quotation policy (Eq. 13) on net profit and satisfaction

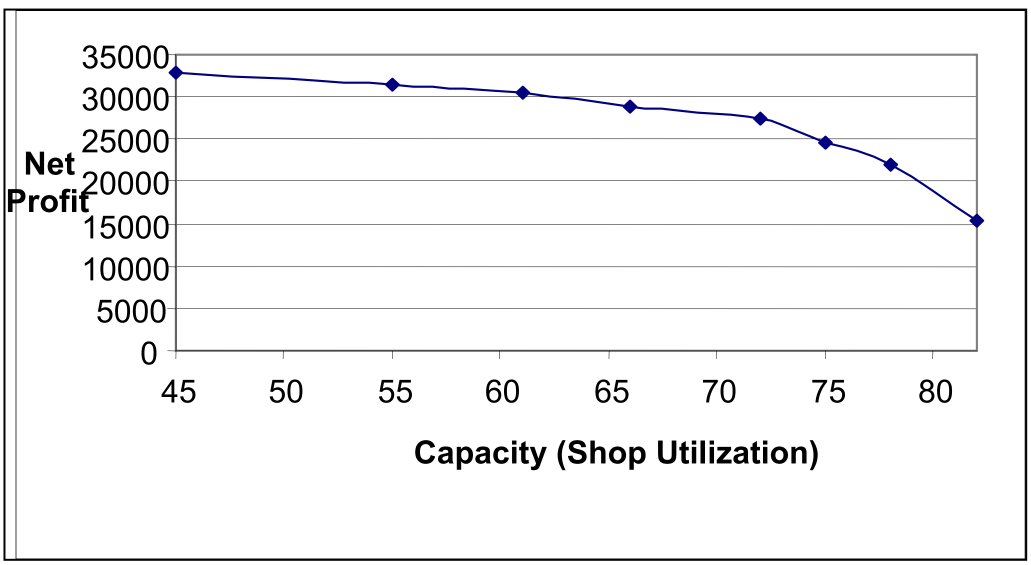

Figure 5: Effect of change in capacity on net profit