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Testing Different Overtime Policies with Different Price and Due Date Negotiation Strategies

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Abstract

Today, organizations use of e-commerce tools for purchasing and sales have developed from e-catalogs and e-mail to e-auctions. This research simulated such a fully automated negotiation system for business transactions to test the best overtime policies to use with different decision rules for price and due date. Software within e-commerce systems negotiates prices and due dates using pre-thought out negotiation strategies. This research tests tested the effect of several overtime policies with different price and due date negotiation strategies. It used a simulation of a job shop and an imaginary market to demonstrate how one can compare different combinations of overtime policies and negotiation strategies in different markets. It extends previous research by including the option of using flexible overtime both at the quotation stage and during shop operation. The research suggested that simulation testing of negotiation and overtime strategies for firms and their markets is a practical way of choosing overtime policies.

Key Words: *E-Negotiation, Demand Management, Due Date Negotiation, Job Shop, overtime.*

Introduction

One aim of e-commerce is to put most business functions on an electronic basis and minimize the use of human time. One repetitive business function involving human time is negotiation. For example, in a typical market with many buyers and sellers, each buyer wants to get the best (to the buyer's firm) combination of specifications, delivery, payment terms, price, and other factors for all of the firm's purchases. Ideally each seller wants to sell its capacity to a combination of buyers that maximizes the selling firm's profits, both in the short term and long term. The most thorough and potentially efficient way to achieve this is for each purchase to be negotiated. These negotiations are complicated as they are often not just two party interactions and have many points of negotiation. To extend the example, each buyer is probably negotiating with several sellers to get the best deal for the buying organization. This may include trying to play one seller off against another. Each seller is probably negotiating its capacity with several buyers and trying to play each buyer off against the other. Peleg, Lee, and Hausman (2002) describe the situation well from the buyer's viewpoint.
Further complications arise because in most business-to-business (B2B) markets the same buyers and sellers often interact over many possible deals over time. Thus, there is a snowball effect in which the result of any negotiation and contract implementation affects subsequent interactions. This reputation effect impacts how other sellers and buyers react during future negotiations. Because of the marked complexity, full negotiation is often used only for important transactions, where the investment of time and money is justified. When the cost of the negotiation is greater than the profit arising from it, firms use less expensive strategies such as standard prices and lead times in e-marketplaces (Harrington 2000, Kilbane 2001, Konicki 2000), auctions (Beam and Segev 1998, Kumar and Feldman 1999, Atkinson 2000, Thomas 2000, Davis 2001, and reverse auctions (Porter 2000a, b).

This paper's premise is that if organizations could inexpensively conduct full negotiation through electronic means then they would benefit greatly (Herniter, Carmel, and Nunamaker 1993). This paper now gives an overview of the current state of e-negotiation research, starting with papers on general e-negotiation before discussing the research backing the particular case this paper studies in detail.

Literature Review

This section first describes what some authors believe is the tools that general and e-negotiation can use. Then it looks at research supporting the specific case of e-negotiation for a job shop with flexible overtime that the paper simulates.

Negotiation Support Systems (NSS)

The most basic type of e-negotiation uses a Negotiation Support System (Lim and Benbaset 1992, Perkens et al. 1996). Rangaswamy and Shell (1997) concluded that parties using a NSS made more integrative agreements, which maximizes the utility of the bargain for all the parties involved. Kersten and Szpakowicz (1998) and Kersten and Noronha (1998) defined a NSS as consisting of two parts, a decision support function and a communication support function. Kersten and Noronha (1999) compared software agents and decision support systems for both distributive (fixed pie) and integrative (jointly benefit) negotiations. They stated that most work has been done on supporting distributive negotiations, whilst most real life negotiations are of both types at different stages in the process. The next more complex tools for e-negotiation are intelligent agents as described by Khoo, Tor, and Lee (1998).

Intelligent Agents

Oliver (1996) considered that if intelligent agents can carry out simple negotiations then many more transactions (like booking hotel rooms) would be negotiated. He stated that such agents should be given initial bargaining strategies then allowed to develop better ones through learning. He suggested that genetic algorithms may be used for these learning mechanisms, and that the use of practice forums would assist in this learning. Goh, Teo, Wu, and Wei (2000) found in experiments that electronic agents obtained outcomes comparable to but not better than unassisted humans in both types of negotiations, integrative and distributive. The next step in complexity for e-negotiation is automated negotiation systems, as described by Sandholm (1999).

Automated Negotiation Systems

Beam and Segev (1996, 1997) defined how automated negotiation could be used within electronic commerce. They stated that there are two main problems; one standard terminology so that intelligent agents speak the same language, and the second is determining how to keep negotiating strategies secret. Zeng and Sycara (1998) discussed the development of autonomous agents capable of learning from experience, where negotiations a sequential activity. They suggested that game theory is too limiting for real life negotiation modeling, especially as more than two parties are normally involved.
Lo and Kersten (1999) reported on negotiation software agents (NSA) that represent their users and can make offers and counter offers. The MIT Media Lab developed a rule-based agent for negotiation in a predefined market with a given set of rules. They used a neutral third party agent with history of previous negotiations to propose agreements beneficial to both parties, as well as a NSS for both parties. Kersten, Noronha, and Teich (2000) believed that what e-commerce really needs is a combination of auctions and traditional bilateral negotiations.
Thus, in this present time of change, where most business-to-business quotation and purchasing, including job shop orders, will be soon done over the web, Anders (1999) stated that firms should have a quotation and negotiation strategy. However, as the market changes so rapidly these strategies have to change rapidly as well. Moreover for make-to-order (MTO) products, price and due date quotation strategies can have an immediate effect on company survival.

For as Kingsman et al. (1996) wrote, "the process of dealing with customer enquiries so as to attract a sufficient load of profitable work is the essential problem for MTO companies". Thus firms should test proposed new negotiation strategies before going online with them.

Demand Management in a Job Shop

There are many methods that a firm could use in the quotation and negotiation process, such as Matsui's (1985) order selection policies, Wang, Yang, and Lee's (1994) neural network approach, Weng's (1996) lead-time rules, Akkan's (1997) finite capacity planning, Kingsman and de Souza's (1997) knowledge based decision support system, Kingsman and Mercer's (1997) strike rate matrices, Litoiu and Tadei's (1997) fuzzy due dates, Blocher et al's (1998) order scheduling in a job shop, Hendry, Kingsman, and Cheung's (1998) workload control, Li, Ip, and Wang's (1998) genetic algorithms, So and Song's (1998) use of delivery time guarantees, Weng's (1998) lead-time management methods, Zapfel's (1998) customer order driven scheduling, Spearman and Zhang's (1999) optimal lead time policies, and Webster's (2002) dynamic pricing and lead-time policies.

Overtime Policy

Buckle and Meads (1991), Dar-El, Sofer, Molcho, and Shtrichman (1991), Lawrence (1994), and Ozdamar and Yazgac (1997) considered that when a job runs late, the firm will complete the tardy order with overtime, subcontracting, or some other method of expedited production.

Adshead and Price (1989) investigated the use of overtime in a make-to-stock shop to find how a change in overtime decision policies alters the cost performance of the shop. They stated that the management of overtime differs from other areas of production control, like scheduling or stock control because of the tendency for much of overtime control to be on an “ad hoc" fire-fighting basis. Adshead and Price reported that there is much anecdotal evidence to show that production managers highly value the ability to adjust the level of overtime quickly. They concluded that a policy to use overtime when a job cannot meet its due date without overtime is preferred to a policy to schedule overtime when the aggregate load on the shop exceeds the shop's capacity. They considered that this is because the first policy needs less overtime and has less stock-out. However, they wrote the one major problem with flexible overtime is that workers dislike rapid variations in overtime.

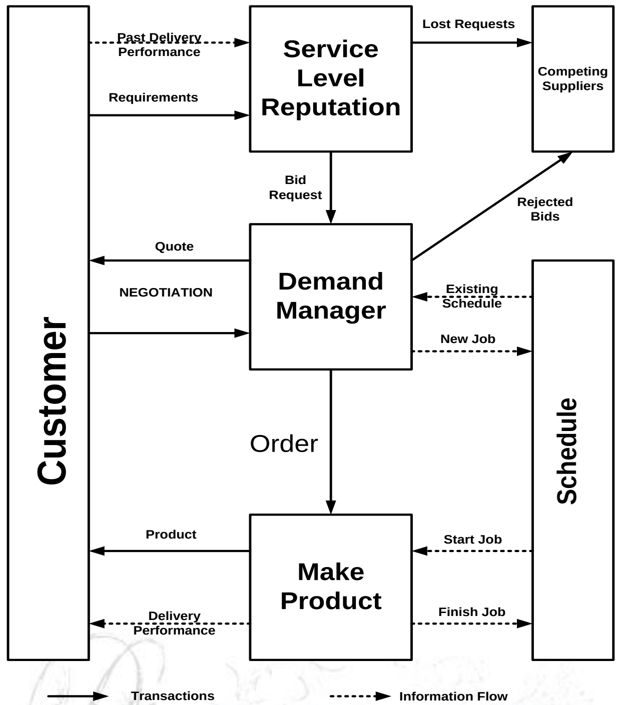
This paper demonstrates that simulation, which has been used extensively to test shop floor rules, can be used to compare and test new negotiation and overtime strategies for both electronic (Croson 1999) and human negotiation. It demonstrates how to carry out such a comparison using Moodie's negotiation simulation of a classic job shop (1999) but with flexible overtime. A major criticism of Moodie's paper is that it ignores this point that shops that are tardy in delivering a job will often use overtime to catch up.

Method and Model

Outline

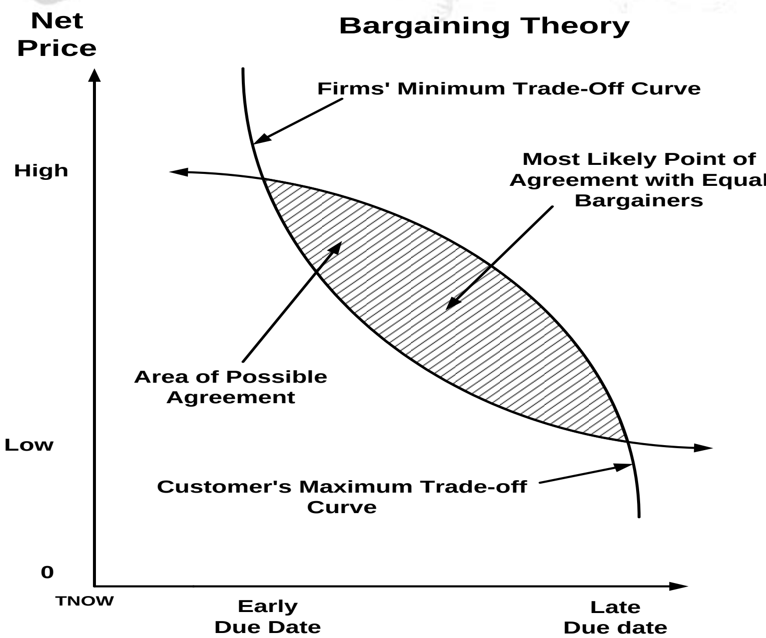
The basic model and terminology for this study is that of Moodie (1999), from which Figure 1 is copied, which simulates the demand management situation for a job shop without the option of overtime where lead-time and price is variable.
As de Treville, Shapiro, & Hameri, (2004) said, firms must give the lead times customers will pay for. The following description is taken from parts of Moodie's paper with changes from that model noted in detail. The demand manager agent performs three tasks in the model. First, the demand manager estimates the firm's maximum price for a given due date curve for the job request. Second, the demand manager must decide on a bargaining approach, which is whether or not to haggle over the price and the due date. The firm replies to the customer's bid request with its initial bid quotation. The demand manager and customer may then negotiate or bargain.

Figure 1



During any negotiation, both the firm and the customer know their own, but not each other's, reservation trade-off curve between price and due date. Figure 2 (copied from Raiffa 1992: 155) shows these trade-off curves for price and due date, with any combination of price and due date within the feasible region could provide the agreed bid result. If there is no feasible region then the customer goes elsewhere for its requirement.

Figure 2



Akkan (1997) writes that "a system that allows rejection of customer orders must facilitate negotiation of delivery times". The model assumes that if the parties finally agree then the agreement is in the center of the feasible region, where both mutually benefit the most.

Third, if the customer places an order then the demand manager places the new job order into the schedule, if used. The research assumes that the firm negotiates only one order at one time; there is no simultaneous negotiation or contingent bidding. The simulation releases the orders to the shop immediately as recommended by Melnyk and Ragatz (1998), Philipoom, and Fry (1992), and Tsai et al. (1997). The model dispatches jobs with the earliest operation due date rule (EODD), as Conway and Maxwell (1962) recommended. The main output measure is net revenue rate, which is the total of the gross revenue for all products that the firm delivers in a period minus variable (to the study) costs including overtime. Normal time labor costs are assumed fixed.
The research assumes arbitrarily that the modeled shop has the flexibility of working overtime on any workcenter at the rate of up to 50% of normal working time with a cost based on increased rates. This 50% increase, for example, represents extending an eight-hour shift to a twelve-hour shift, using the same labor and is a significant increase in available capacity. When an operation is running behind its planned start time, then the firm can use overtime on that operation as necessary to get that operation back on schedule. The model charges the cost of that overtime, at an overtime charge rate of OTCR, against the net revenue for that period. The overtime used is the lesser of the amount that the job is tardy or the availability of overtime for that workstation. The problem is when to consider that a job is running tardy and thus needs overtime.

The demand manager, especially if an electronic agent, must know how to conduct each of these tasks. In other words, the firm must have a negotiation strategy. With overtime, a negotiation strategy consists of five parts. The first is deciding what due date estimation method to use. The second is deciding what overtime policy to adopt. The third is deciding what overtime scheduling rule the shop floor should follow. The fourth is deciding over what factors, price and due date, to bargain. The fifth is deciding on the values of management options, such as normal time and overtime charge rates. We shall discuss the first three tasks next.

Due Date Estimation

The demand manager must choose a due date estimation method to compute early due dates, based on the expected processing times (EPTs) for each workstation that the potential job would visit and present time (TNOW). The simulation's actual operation processing times differ from the expected processing times. The experiments use the five due date estimation methods that dominated in Moodie's research.

Table 1 - ***Previously Suggested Due Date Estimation Methods***

Name	***#***	***Acronym***	***Due Date Estimation Equation***	***Reference***
Total Work	1	TWK	FEDD = TNOW + TEPT * $(1 + \underline{QL})$	Conway, Maxwell, & Miller [57]
Work in System	2	WIS	FEDD = TNOW + TEPT + $\underline{EPT} * \Sigma_i \{1 + QL_i\}$	Salegna [62]
where EPT is expected operation processing time TEPT is total expected processing time for a job, QL is expected queue length, i is job operation number, $\underline{X}$ is the mean for value X for all requirements.				

The first two due date estimation methods are based on finite capacity schedules, described by Vig and Dooley (1991). They are either LFN (forward loading) or SFN (forward scheduling). With forward loading, the scheduler adds up the little slices of spare time on a machine schedule that occur after the earliest start date of the job until the total is more than the expected processing time for that operation.

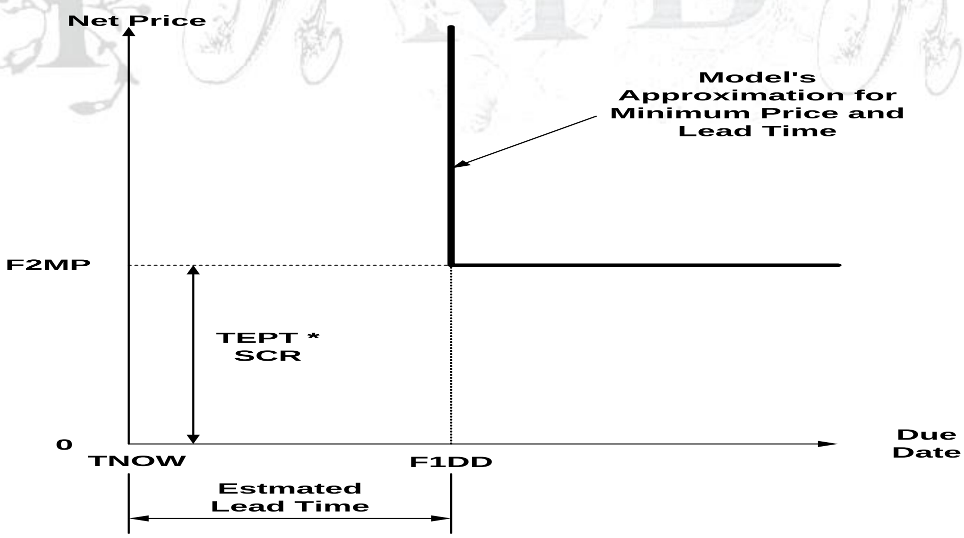
That time becomes the expected finishing time for the operation. With forward scheduling, the scheduler fits the job's operation into the first gap larger than the expected processing time to produce the expected finishing time. The simulation does not move already scheduled operations to fit in a new operation. Table 1 details the two previously suggested simple due date estimation methods used.

The other due date estimation method used is aggregate loading (AGL). AGL uses a rough, aggregate schedule, which consists of segments of time or buckets containing previously loaded jobs. The capacity of a bucket is the sum of each workcenters' capacity. AGL forward loads the new job into unfilled time buckets from TNOW, until the number of time buckets loaded equal or surpasses the job's TEPT. For example, if a job's TEPT is 5.6, then the planned due date is when the program finishes loading that job into six time buckets.

Overtime Policies

The previous research's (Moodie 1999) results represent a no overtime policy (Policy 0), which is the base case for comparison. The paper now describes policies that use overtime in detail tested in the simulation. Each policy results in a different way of determining the firm's minimum price for a given due date trade-off curve.
The first two policies are ones that ignore overtime at the quotation stage, but then uses overtime in an emergency manner to make sure tardy jobs finish on time. The research tries this both with a full bargaining and a price only bargaining approach. The first (Policy 1) with a price only bargaining approach, results in the simple L-shaped curve of Figure 3 and uses, based on a standard charge rate (SCR), total expected processing time (TEPT), one price (F2MP = SCR * TEPT), and one estimated due date (F1DD).

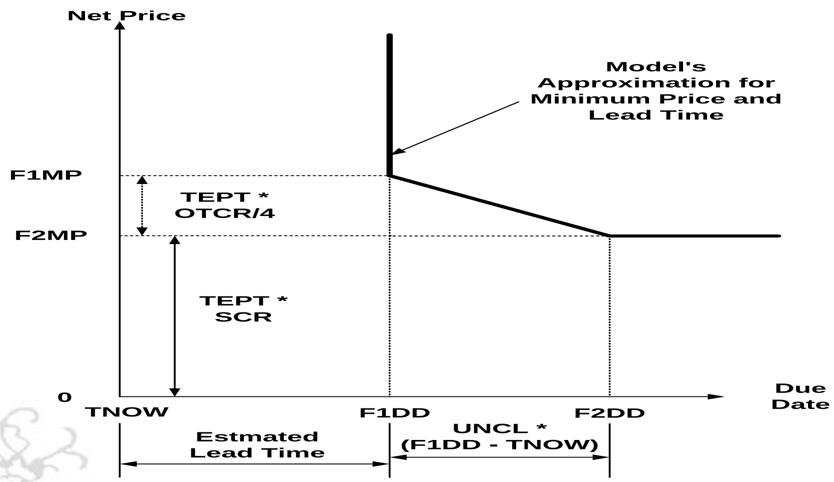
Figure 3
Firm's Minimum Net Price to Due Date Trade-off Curve
For Policy One - Price Only Bargaining with Overtime



The second (Policy 2), where the firm also bargains about the due date, results in the three-part curve of Figure 4. The curve involves estimating two due-dates. The first due date (F1DD) assumes that there is a 50% chance of using overtime. The first due date requires a price (F1MP), which includes a premium to the minimum price, based on a quarter of the overtime charge rate (OTCR) multiplied by TEPT. The quarter is derived from a 50% overtime allowance that is 50% likely to be used, which are both arbitrarily chosen.

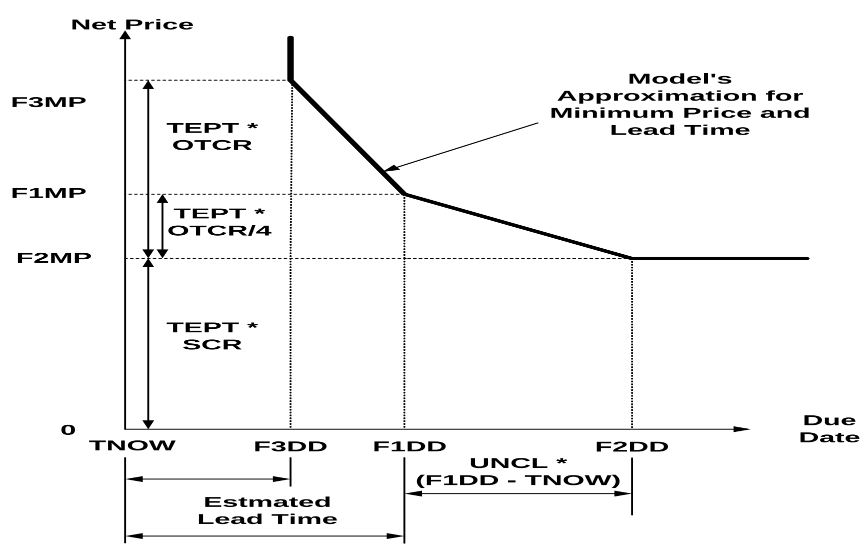
The second internal due-date (F2DD) adds the uncertainty allowance (UNCL) multiplied by estimated lead time to obtain a later time that is unlikely to need overtime. A diagonal line connecting point {F1DD, F1MP} to point {F2DD, F2MP} shows the trade-off line between these two due dates.

Figure 4
Firm's Minimum Net Price to Due Date Trade-off Curve
For Policy Two - Full Bargaining with Overtime but No Overtime in Quotes



The third (Policy 3) uses planned overtime in the quotation process if the customer rejects the original quotation and uses full bargaining. However, the policy also involves a further step in the negotiation process. If the customer rejects the original quotation because of too late a due date, then the model calculates a new internal early due date, which is based on completing the job using only overtime. This represents either doing the job completely in overtime or more likely bumping other jobs into overtime in order to complete this job. The simulation repeats the negotiation stage with the new earlier due date (F3DD) but increases the price rate by the overtime surcharge rate (OTCR * TEPT). This generates the firm's new minimum trade-off curve of Figure 5. The minimum price (F3MP) for F3DD is F3MP + OTCR * TEPT. A diagonal line connecting point {F1DD, F1MP} to point {F3DD, F3MP} is the extra part of the trade-off.

Figure 5
Firm's Minimum Net Price to Due Date Trade-off Curve
For Policy Three - Full Bargaining with Overtime in Quotes



The four policies are listed in Table 2.

Table 2 - ***The Composition of the Different Overtime Policies***

Policy	*Use Overtime*	*Bargain on Due Date*	*Use Overtime in Quotation*
0	No	Yes	No
1	Yes	No	No
2	Yes	Yes	No
3	Yes	Yes	Yes

Overtime Scheduling Rules

The research uses four possible overtime shop floor scheduling rules that can schedule overtime when a job is likely to be tardy. The first rule (A), delayed next operation (DNO), is that if a job will finish (using actual processing time) after its scheduled start time for its next operation (or its delivery due date if it is in its last stage), then schedule overtime. The amount the job will be tardy starting the next required operation (or being delivered if at its last stage), is the amount the job is tardy for the present operation. This rule is often impossible to apply, as it requires the shop to have knowledge of future unknowns. However, the experiments use it to show what effect perfect future knowledge would have

The second rule (B), called late operation start (LOS), is that if a job starts late, and then schedule overtime. The amount the operation is tardy in starting an operation is the amount the job is tardy for that operation.

The third rule (C), called late operation finish (LOF), is that if a job finishes after its scheduled finish time for that operation then schedule overtime. The amount the operation finishes tardy is the amount the job is tardy.

The fourth rule (D), expected delay to next operation (EDN), is that if a job is expected (using expected processing time) to finish after its scheduled start time for its next operation (or its delivery due date if it is in its last stage) then schedule overtime. The amount the operation is expected to be tardy starting the next required operation (or being delivered if at its last stage) is the amount the job is tardy for the existing operation.

These four rules are derived from results of two decisions. The first decision is can the shop floor controller use the actual processing time (APT), as opposed to the expected processing time. The second decision is should the shop floor controller consider the next operation's planned start time (NOP). The four rules answer the two decisions, as follows in Table 3.

Table 3 - ***Different Shop Floor Overtime Rules***

Name	*Designation*	*Acronym*	*Use APT*	*Use NOP*
Delayed Next Operation	A	DNO	Yes	Yes
Late Operation Start	B	LOS	No	No
Late Operation Finish	C	LOF	Yes	No
Expected Delay to Next operation	D	EDN	No	Yes

The main output measure, as in Moodie (1999), is net revenue rate, which is the total of the gross revenue for all products that the firm delivers in a period minus variable costs including overtime. Normal time labor costs are assumed fixed. The adjusted model assumes arbitrarily that the modeled shop has the flexibility of working overtime on any workcenter at the rate of up to 50% of normal working time with a cost based on increased rates.

Demonstration Experiment

All statistical decisions such as run lengths, which are based on Fishman's (1978) method number of simulation runs (30 per each situation), random number seeds, choice of variables, etc. are as in Moodie's (1999) paper. The initial experiments assisted in the selection of suitable arbitrary high and low values for each of nine variables that set each scenario.

The next experiment used these choices of high and low values for each market scenario variable to predict the four most influential variables, and thus determined the sixteen test market scenarios for the main experiment. Each of these sixteen test scenarios has a label of four letters, where each letter represents the level of a variable value for a scenario dimension. These letters are "H" for runs with the high value of the variable and "L" for those using the low value of the variable. Table 4 shows the low and high variable values for each varied scenario dimension (with mean acronym in brackets).

Table 4 - ***Value of Scenario Dimension Levels***

Dimension	***Acronym***	***LOW Value***	***HIGH***	***Units***
Demand	AIAT	1	2	time
Accuracy	PERR	10	50	% (TEPT)
Premium	PREM	2	6	money/EPT
Responsiveness	RESP	3	9	time/EPT

They are in sequence of importance: demand, represented by average inter-arrival time (AIAT); accuracy, represented the average error in estimating processing times (PERR); premium, represented by the average premium rate that customers will pay extra for early delivery (PREM; and responsiveness, represented by how short a lead time customers want on average (RESP). For example, the scenario acronym LLHL represents where AIAT is 1, the low value; PERR is 0.1, the low value; PREM is 6, the high value; and RESP is 3, the low value.

The main experiment has several objectives. The first objective is to find the set of values for the management options for each combination of test scenario, due date estimation method, and bargaining approach, that maximizes the net revenue rate. The second objective is to find the best negotiation strategy for each test scenario, which is the combination of due date estimation method, bargaining approach, and values of the management option that maximizes the net revenue rate.

The third objective is to examine the consequences of sub-optimal choices for the management options. The fourth objective is to examine the selection of due date estimation methods in the context of scenario dimensions. An inferior choice for any part of a negotiating strategy gives a lower net revenue rate, whatever the choices for the other parts in all scenarios. The demand manager can therefore ignore any inferior choice in future decisions.

Most combinations of due date estimation methods and bargaining approaches require that the demand manager select values for the management options. The experimenter must therefore decide how many different and what values to use for these options. Early runs of the main experiment suggest that it should use a minimum of eleven values of UNCL, five values of SCR, and six values of OTCR. As the plots of revenue rates versus the value of a particular management option show a raise, the experimenter tests extra values of management options in the direction of increasing revenue until the net revenue rate starts to fall. So some combinations of method, approach, and scenario require the use of extra values.

This experiment compares three policies (and the base policy for which the results already exist), four rules, five methods, and sixteen test scenarios. This gives sixty combinations of method, policy, and rule for each scenario. Each combination is compared to the base policy results for its scenario. For each combination and scenario, the demand manager has to make a decision on the charge rates and, if needed, the extra uncertainty time allowance for each job to maximize the net revenue rate. The data for thirty simulation runs is recorded for each combination and scenario using these values to allow a full statistical investigation of the results. The next section summarizes the voluminous results.

Summarized Results

Preferred Strategies

Table 5 shows the abbreviations used in reporting the simulation results.

Table 5 – *Abbreviations used in results*

Policy	*Num.*	*Overtime Policy*	*Rule*	*Letter*	*Overtime Rule*	*Method*	*Scheduling method*
B	**0**	No overtime	**DNO**	**A**	Overtime with allowance	**AGL**	Aggregate Loading
O	**1**	Overtime with no allowance.	**LOS**	**B**	Overtime with no allowance	**JTW**	TWK + JIQ
OB	**2**	Overtime with allowance	**LOF**	**C**	Overtime with no allowance	**LFN**	Forward Loading, No move
OBQ	**3**	Quote overtime jobs	**EDN**	**D**	Overtime with no allowance	**SFN**	Forward Scheduling, No move
						TWK	Total Work

Tables 6 – 21 show the detailed results for each scenario with the highest revenue rate in bold, together with the best and second best combination of scheduling method and overtime policy.

Table 6 – *Individual Revenue Rate results of each simulation for Scenario 1 – LLLL*

	Policy													
Method	***O***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	68.8	69.9	70.6	70.6	69.9	69.5	70.1	70.2	69.4	72.4	72.2	71.2	72.3	72.4
JTW	71.6	70.0	73.0	70.0	69.2	70.4	71.1	70.4	74.0	74.7	**81.2**	77.9	74.0	81.2
LFN	68.9	64.4	63.0	56.9	62.2	69.8	70.5	66.8	69.3	70.0	71.4	67.7	69.4	71.4
SFN	67.2	63.8	62.1	55.4	60.7	69.2	69.8	67.6	68.6	69.0	70.9	66.3	68.5	70.9
TWK	67.9	65.8	72.3	63.9	63.8	70.3	74.2	69.4	69.4	69.0	73.4	69.6	69.4	74.2
Best	*71.6*	*70.0*	*73.0*	*70.6*	*69.9*	*70.4*	*74.2*	*70.4*	*74.0*	*74.7*	*81.2*	*77.9*	*74.0*	*81.2*
Best combination is Method JT with Policy 3B							**2nd Best Combination is Method JTW with Policy3C**							

Table 7 – *Individual Revenue Rate results of each simulation for Scenario 2 – LLLH*

	Policy													
Method	***O***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	77.1	70.3	70.6	70.6	70.3	69.6	68.8	68.8	69.0	78.7	78.7	78.5	78.6	78.7
JTW	76.2	76.0	76.2	75.9	75.9	75.2	75.2	75.1	80.4	80.6	**88.3**	86.4	80.4	88.3
LFN	74.3	72.6	73.4	69.4	72.3	75.8	76.7	74.7	75.7	75.9	77.7	74.7	75.5	77.7
SFN	74.0	73.7	73.9	69.4	72.5	75.9	76.8	74.6	75.6	75.9	77.8	74.1	75.5	77.8
TWK	77.6	79.2	82.1	60.8	78.2	77.4	80.0	76.9	76.9	76.4	80.2	76.7	76.6	82.1
Best	*77.6*	*79.2*	*82.1*	*75.9*	*78.2*	*77.4*	*80.0*	*76.9*	*80.4*	*80.6*	*88.3*	*86.4*	*80.4*	*88.3*
Best Combination is Method JTW with Policy 3B							**2nd Best Combination is Method JTW with Policy 3C**							

Table 8 – *Individual Revenue Rate results of each simulation for Scenario 3 – LLHL*

	Policy													
Method	***O***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	79.8	64.4	63.0	62.8	63.7	73.8	72.9	72.7	73.3	85.9	84.9	83.5	85.0	85.9
JTW	83.6	82.9	86.2	82.6	81.6	83.5	84.4	83.3	85.1	86.1	**90.7**	86.4	85.1	90.7
LFN	80.2	76.7	75.0	68.2	73.8	81.7	82.3	75.8	80.6	81.5	82.5	77.6	79.9	82.5
SFN	77.0	76.0	74.0	66.6	72.9	80.1	80.7	78.1	79.1	79.0	80.3	75.0	78.4	80.7
TWK	78.1	79.3	86.6	77.2	77.2	82.7	88.6	81.2	81.2	80.9	87.4	81.1	81.3	88.6
Best	*83.6*	*82.9*	*86.6*	*82.6*	*81.6*	*83.5*	*88.6*	*83.3*	*85.1*	*86.1*	*90.7*	*86.4*	*85.1*	*90.7*
Best Combination is Method JTW with Policy 3B							**2nd Best Combination is Method TWK with Policy 2B**							

Table 9 – *Individual Revenue Rate results of each simulation for Scenario 4 – LLHH*

	Policy													
Method	***O***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	93.6	82.8	82.4	82.2	82.5	83.4	82.6	82.8	82.8	96.5	94.2	93.9	93.8	96.5
JTW	92.3	92.6	92.9	92.6	92.5	90.0	90.3	90.0	96.1	96.6	**102.4**	99.8	96.1	102.4
LFN	89.8	89.1	89.6	84.5	88.0	90.5	91.5	88.2	89.9	90.6	92.5	88.3	90.3	92.5
SFN	88.4	89.6	89.3	84.5	87.4	90.7	91.8	88.5	89.7	90.2	92.3	88.0	90.0	92.3
TWK	94.0	96.7	101.0	95.8	95.8	95.6	97.2	95.0	95.0	95.0	97.5	95.1	95.3	101.0
Best	*94.0*	*96.7*	*101.0*	*95.8*	*95.8*	*95.6*	*97.2*	*95.0*	*96.1*	*96.6*	*102.4*	*99.8*	*96.1*	*102.4*
Best Combination is Method JTW with Policy 3B							**2nd Best Combination is Method TWK with Policy 1B**							

Table 10 – ***Individual Revenue Rate results of each simulation for Scenario 5 - LHLL***

	Policy													
Method	***O***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	59.4	45.5	42.3	41.6	44.8	56.2	55.2	55.1	55.0	66.2	64.5	63.2	64.9	66.2
JTW	64.9	61.6	65.0	60.0	58.5	64.5	65.2	64.7	65.2	66.7	**71.4**	68.3	65.2	71.4
LFN	59.6	54.2	52.9	47.5	51.5	63.7	64.8	60.5	62.5	63.0	64.7	61.5	61.4	64.8
SFN	58.0	54.1	51.5	46.4	50.8	62.0	63.5	61.8	61.3	61.5	63.7	60.0	60.2	63.7
TWK	57.2	57.2	60.8	53.5	53.5	61.5	64.4	59.6	59.6	59.6	62.6	59.8	59.7	64.4
Best	*64.9*	*61.6*	*65.0*	*60.0*	*58.5*	*64.5*	*65.2*	*64.7*	*65.2*	*66.7*	*71.4*	*68.3*	*65.2*	*71.4*
Best Combination is Method JTW with Policy 3B							**2nd Best Combination is Method JTW with Policy 3C**							

Table 11 – *Individual Revenue Rate results of each simulation for Scenario 6 - LHLH*

	Policy													
Method	***O***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	69.6	67.0	67.2	67.2	66.9	63.5	62.4	63.6	63.2	72.6	72.8	72.1	72.0	72.8
JTW	70.2	70.1	70.7	70.2	70.1	68.0	68.3	68.2	72.3	72.7	**79.4**	77.6	72.3	79.4
LFN	65.5	64.4	66.0	62.7	63.5	70.1	71.6	68.9	69.2	69.6	71.6	69.1	68.5	71.6
SFN	64.0	64.7	66.2	62.6	64.3	69.9	71.6	69.4	69.1	68.9	71.5	68.4	68.4	71.6
TWK	68.4	70.6	73.2	68.3	68.3	69.8	70.7	68.9	68.9	68.8	70.7	68.9	68.8	73.2
Best	*70.2*	*70.6*	*73.2*	*70.2*	*70.1*	*70.1*	*71.6*	*69.4*	*72.3*	*72.7*	*79.4*	*77.6*	*72.3*	*79.4*
Best Combination is Method JTW with Policy3B							**2nd Best Combination is Method JTW with Policy 3C**							

Table 12 – *Individual Revenue Rate results of each simulation for Scenario 7 - LHHL*

	Policy													
Method	***O***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	69.2	54.6	51.4	49.9	53.3	64.7	63.0	62.9	63.4	76.6	74.7	72.6	75.8	76.6
JTW	75.5	72.6	76.3	70.9	69.4	75.5	77.3	75.5	74.0	76.2	**80.2**	76.1	74.0	80.2
LFN	68.8	65.0	63.6	56.6	61.6	73.7	74.7	66.7	71.4	72.6	73.6	68.8	70.6	74.7
SFN	66.5	64.6	62.0	55.5	60.9	72.0	72.1	69.6	69.2	70.4	72.1	67.0	68.5	72.1
TWK	69.0	69.2	73.8	64.7	64.7	72.6	76.2	69.1	69.1	69.1	75.1	69.6	69.1	76.2
Best	*75.5*	*72.6*	*76.3*	*70.9*	*69.4*	*75.5*	*77.3*	*75.5*	*74.0*	*76.6*	*80.2*	*76.1*	*75.8*	*80.2*
Best Combination is Method JTW with Policy 3B							**2nd Best Combination is Method JTW with Policy 2B**							

Table 13 – *Individual Revenue Rate results of each simulation for Scenario 8 - LHHH*

	Policy													
Method	***O***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	84.2	75.1	74.8	75.0	74.9	75.7	75.0	74.9	75.4	87.0	87.3	85.8	86.6	87.3
JTW	84.3	84.6	85.1	84.6	84.4	82.7	83.5	83.3	86.1	86.7	**92.3**	90.5	86.1	92.3
LFN	78.8	79.2	80.6	76.4	78.4	82.9	85.1	81.2	81.9	82.9	85.3	81.7	81.4	85.3
SFN	77.3	79.7	80.3	76.1	77.8	83.0	84.7	82.0	81.3	81.7	84.4	80.6	80.5	84.7
TWK	84.7	85.3	89.1	83.3	83.4	86.0	88.3	83.9	83.9	84.3	87.7	84.3	84.4	89.1
Best	*84.7*	*85.3*	*89.1*	*84.6*	*84.4*	*86.0*	*88.3*	*83.9*	*86.1*	*87.0*	*92.3*	*90.5*	*86.6*	*92.3*
Best Combination is Method JTW with Policy 3B							**2nd Best Combination is Method JTW with Policy 3C**							

Table 14 – *Individual Revenue Rate results of each simulation for Scenario91 - HLLL*

	Policy													
Method	***O***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	50.1	35.4	32.7	31.9	33.6	45.3	45.0	45.2	45.0	49.1	49.3	48.9	48.9	50.1
JTW	49.4	49.3	48.0	46.1	47.1	49.6	49.6	49.6	52.9	53.8	**53.8**	53.1	52.9	53.8
LFN	49.7	46.0	43.1	38.8	43.5	49.2	49.1	47.8	48.9	49.9	50.0	48.4	49.6	50.0
SFN	48.5	45.3	42.0	38.0	43.1	48.6	48.6	48.3	48.3	49.1	49.6	47.4	48.9	49.6
TWK	50.8	48.3	50.5	46.8	46.8	51.9	52.7	51.6	51.6	51.6	52.6	52.3	52.4	52.7
Best	*50.8*	*49.3*	*50.5*	*46.8*	*47.1*	*51.9*	*52.7*	*51.6*	*52.9*	*53.8*	*53.8*	*53.1*	*52.9*	*53.8*
Best Combination is Method JTW with Policy 3B							**2nd Best Combination is Method JT with Policy 3A**							

Table 15 – *Individual Revenue Rate results of each simulation for Scenario 10 - HLLH*

	Policy													
Method	***0***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	55.5	48.7	48.4	47.9	48.6	49.7	50.1	50.2	49.5	52.3	53.0	52.9	52.2	55.5
JTW	54.7	55.1	54.9	54.9	54.9	53.5	53.5	53.3	56.5	56.7	56.6	56.6	56.5	56.7
LFN	54.3	52.2	51.4	48.9	51.0	53.1	53.0	52.6	52.9	53.6	53.9	53.0	53.7	54.3
SFN	53.8	51.9	51.0	48.1	50.6	52.8	52.9	52.9	52.9	53.3	53.7	52.3	53.1	53.8
TWK	**57.2**	56.9	56.9	56.4	56.4	56.2	56.3	56.2	56.2	56.2	57.1	57.0	57.0	57.2
Best	*57.2*	*56.9*	*56.9*	*56.4*	*56.4*	*56.2*	*56.3*	*56.2*	*56.5*	*56.7*	*57.1*	*57.0*	*57.0*	*57.2*
Best Combination is Method TWK with Policy O							**2nd Best Combination is Method TWK with Policy 3B**							

Table 16 – ***Individual Revenue Rate results of each simulation for Scenario 11 – HLHL***

	Policy													
Method	***0***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	57.4	46.2	42.3	40.6	44.8	53.3	53.2	52.9	53.2	56.9	56.5	55.5	56.7	57.4
JTW	57.5	57.2	55.6	53.9	54.9	57.4	57.3	57.1	59.5	60.5	**60.3**	59.2	59.5	60.5
LFN	56.6	53.7	50.4	45.9	51.3	56.9	56.5	54.2	56.2	56.8	57.3	54.7	56.7	57.3
SFN	55.3	53.1	49.2	44.5	50.3	55.9	55.9	55.1	55.4	56.1	56.2	53.5	55.2	56.2
TWK	58.8	56.6	59.2	55.1	55.1	59.7	60.3	59.3	59.3	59.1	61.7	59.6	59.7	61.7
Best	*58.8*	*57.2*	*59.2*	*55.1*	*55.1*	*59.7*	*60.3*	*59.3*	*59.5*	*60.5*	*61.7*	*59.6*	*59.7*	*61.7*

Best Combination is Method TWK with Policy 3B | **2nd Best Combination is Method JTW with Policy 3A**

Table 17 – ***Individual Revenue Rate results of each simulation for Scenario 12 – HLHH***

	Policy													
Method	***0***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	65.2	57.6	57.2	56.7	57.3	58.9	59.2	59.3	58.8	61.4	61.8	61.7	61.3	65.2
JTW	64.2	64.6	64.4	64.1	64.2	63.1	63.0	62.9	65.4	65.8	65.6	65.5	65.4	65.8
LFN	63.3	61.8	60.6	57.9	60.5	62.6	62.4	61.0	62.2	62.4	63.1	61.5	62.5	63.3
SFN	62.5	61.6	60.1	57.4	60.0	62.2	61.8	61.7	61.6	61.9	62.5	60.7	61.8	62.5
TWK	**67.2**	66.7	67.1	66.1	66.1	65.9	65.9	65.8	65.8	65.8	66.9	66.5	66.7	67.2
Best	*67.2*	*66.7*	*67.1*	*66.1*	*66.1*	*65.9*	*65.9*	*65.8*	*65.8*	*65.8*	*66.9*	*66.5*	*66.7*	*67.2*

Best Combination is Method TWK with Policy O | **2nd Best Combination is Method TWK with Policy 1B**

Table 18 – ***Individual Revenue Rate results of each simulation for Scenario 13 – HHLL***

	Policy													
Method	***0***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	45.5	26.3	24.8	25.3	25.9	39.6	39.0	39.9	39.0	44.9	44.8	44.1	44.9	45.5
JTW	47.4	44.0	41.5	38.8	39.9	47.2	47.1	47.0	48.5	49.7	**50.1**	48.8	48.5	50.1
LFN	44.7	38.8	35.8	32.3	35.9	45.8	46.1	43.8	45.1	45.5	46.0	43.9	44.8	46.1
SFN	43.5	38.3	34.8	31.0	35.0	44.8	44.9	44.6	44.3	44.8	45.3	42.9	43.8	45.3
TWK	46.7	42.7	44.9	40.0	40.0	48.0	48.7	46.8	46.8	46.8	47.5	46.6	46.7	48.7
Best	*47.4*	*44.0*	*44.9*	*40.0*	*40.0*	*48.0*	*48.7*	*47.0*	*48.5*	*49.7*	*50.1*	*48.8*	*48.5*	*50.1*

Best Combination is Method JTW with Policy 3B | **2nd Best Combination is Method JTW with Policy 3A**

Table 19 – ***Individual Revenue Rate results of each simulation for Scenario 14 – HHLH***

	Policy													
Method	***0***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	54.1	44.6	43.6	42.9	44.1	47.0	47.1	47.2	46.7	49.7	50.0	50.0	49.3	54.1
JTW	52.8	53.0	52.8	52.4	52.4	50.9	50.9	50.9	54.5	54.9	**55.1**	55.0	54.5	55.1
LFN	50.3	46.9	46.2	43.9	45.6	50.1	50.5	49.1	49.9	49.9	50.4	49.2	49.4	50.5
SFN	49.4	47.0	46.1	43.6	45.4	49.6	50.1	49.7	49.2	49.6	50.1	48.8	49.0	50.1
TWK	54.4	53.4	54.4	51.5	51.5	53.3	53.9	53.0	53.0	52.9	53.7	53.3	53.2	54.4
Best	*54.4*	*53.4*	*54.4*	*52.4*	*52.4*	*53.3*	*53.9*	*53.0*	*54.5*	*54.9*	*55.1*	*55.0*	*54.5*	*55.1*

Best Combination is Method JTW with Policy 3B | **2nd Best Combination is Method JTW with Policy 3C**

Table 20 – Individual Revenue Rate results of each simulation for Scenario 15 - HHHL

Policy													
0	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
51.5	39.0	35.0	33.4	37.9	48.6	47.7	47.1	47.7	52.6	51.1	49.8	52.0	52.6
54.4	51.3	48.4	46.1	47.2	54.5	54.2	53.8	53.8	55.6	55.5	53.7	53.8	55.6
50.4	46.0	42.5	38.3	42.7	53.0	52.3	48.6	51.3	51.8	52.2	48.9	50.7	53.0
49.0	46.1	41.4	37.6	41.9	51.6	51.1	50.3	50.1	50.7	50.8	47.7	49.5	51.6
53.2	50.1	53.2	47.2	47.1	54.9	**56.0**	53.0	53.0	52.9	55.2	52.5	52.8	56.0
54.4	*51.3*	*53.2*	*47.2*	*47.2*	*54.9*	*56.0*	*53.8*	*53.8*	*55.6*	*55.5*	*53.7*	*53.8*	*56.0*
Best Combination is Method TWK with Policy 2B							**2nd Best Combination is Method JTW with Policy 3A**						

Table 21 – ***Individual Revenue Rate results of each simulation for Scenario 16 - HHHH***

	Policy													
Method	***0***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	62.9	53.2	51.7	51.3	53.0	55.5	55.5	53.8	55.2	58.3	58.7	58.5	58.2	62.9
JTW	61.7	62.1	61.7	61.2	61.5	60.3	60.2	60.2	62.6	63.3	63.4	63.0	62.6	63.4
LFN	58.4	56.2	55.4	52.7	54.4	59.4	59.4	57.1	58.1	58.7	59.2	57.3	57.8	59.4
SFN	57.4	55.5	54.8	52.2	54.3	58.7	58.6	58.0	57.6	57.9	58.5	56.5	57.1	58.7
TWK	64.1	62.8	**64.1**	60.7	60.7	63.4	64.1	62.6	62.6	62.5	64.1	62.8	62.8	64.1
Best	*64.1*	*62.8*	*64.1*	*61.2*	*61.5*	*63.4*	*64.1*	*62.6*	*62.6*	*63.3*	*64.1*	*63.0*	*62.8*	*64.1*
Best Combination is Method TWK with Policy 1B							**2nd Best Combination is Method TWK with Policy O**							

Table 22 shows highest net revenue average earning combinations of due date estimation method, overtime policy, and overtime rule for each test scenario.

Table 22 – ***Average Revenue Rate results of all simulations for all Scenarios***

	Policy													
Method	***0***	***1A***	***1B***	***1C***	***1D***	***2A***	***2B***	***2C***	***2D***	***3A***	***3B***	***3C***	***3D***	***Best***
AGL	65.2	55.0	53.6	53.1	54.5	59.6	59.2	59.2	59.2	66.3	65.9	65.1	65.8	67.5
JTW	66.3	65.4	65.8	64.0	64.0	65.4	65.7	65.3	67.9	68.8	**71.6**	69.9	67.9	71.6
LFN	63.4	60.5	59.3	55.1	58.5	64.9	65.4	62.3	64.1	64.7	65.7	62.9	63.9	65.9
SFN	62.0	60.3	58.7	54.3	58.0	64.2	64.7	63.3	63.3	63.8	65.0	61.8	63.0	65.1
TWK	65.6	65.0	68.1	62.0	63.0	66.8	68.6	65.8	65.8	65.7	68.3	66.0	66.0	69.4
Best	**66.3**	**65.4**	**68.1**	**64.0**	**64.0**	**66.8**	**68.6**	**65.8**	**67.9**	**68.8**	**71.6**	**69.9**	**67.9**	**71.6**
Mean	67.3	66.3	68.5	64.7	64.6	67.3	68.8	66.8	67.9	68.8	71.9	70.0	68.2	71.9
Best Combination is Method JTW with Policy 3B							**2nd Best Combination is Method JTW with Policy 3C**							

Table 23 shows the best and second best combination of method and policy for each scenario for maximizing ner revenue rate. Overall, method JTW is the favorite with policy 3 and rule LOS (B). This combination is the best for all busy market scenarios, as well as most unrewarding markets. In twelve scenarios, it is best to bargain, use overtime for tardy jobs, and use overtime in quotations with policy 3. In two scenarios (15, 16), it is best to bargain and use overtime for tardy jobs but not for quotations with policy 2. In the two slack, deterministic scenarios with high responsiveness required (10, 12), it is best to bargain but not to use overtime with policy 0. It is always best to bargain about due dates. In the fourteen scenarios that use overtime, the best shop floor overtime rule is LOS (rule B), which is also the simplest to calculate.

Table 23 – *The Highest Net Revenue Negotiation Strategies for Each Scenario*

	PREM	***Low***	***Low***	***High***	***High***
AIAT	***RESP*** ***PERR***	***Low***	***High***	***Low***	***High***
Low	***Low***	LLLL 1 **JTW/3B** JTW/3C	LLLH 2 **JTW/3B** JTW/3C	LLHL 3 **JTW/3B** TWK/2B	LLHH 4 **JTW/3B** TWK/1B
Low	***High***	LHLL 5 **JTW/3B** JTW/3C	LHLH 6 **JTW/3B** JTW/3C	LHHL 7 **JTW/3B** JTW/2B	LHHH 8 **JTW/3B** JTW/3C
High	***Low***	HLLL 9 **JTW/3B** JTW/3A	HLLH 10 **TWK/0** TWK/3B	HLHL 11 **TWK/3B** JTW/3A	HLHH 12 **TWK/0** TWK/1B
High	***High***	HHLL 13 **JTW/3B** JTW/3A	HHLH 14 **JTW/3B** JTW/3C	HHHL 15 **TWK/2B** JTW/3A	HHHH 16 **TWK/2B** TWK/0

Key; L = Low; H = High

AIAT/PERR/PREM/RESP Scenario Number
Second Best Strategy

Best Strategies Advantage

Table 24 shows the difference in revenue rate between the first and second best combinations for each scenario. This difference is notable except in Scenarios 9, 12, and 16. However, the difference between the best due date estimation method's highest revenue rate and that of the second best method's highest is always statistically significant, usually at a 99.9% level. As in previous research (Moodie, 1999) with no overtime, methods JTW or TWK are always the best for due date estimation. TWK is only the best in slack markets, especially where customers are prepared to pay most for early delivery. The best charge rate values are related to scenario rather than to overtime policy or to negotiation strategy. The value of uncertainty allowance does not seem to significantly affect the results as long as a value in the range 0.3 to 3.3 is used.

Table 24 - *Difference in Revenue Rate between Best and Second Best Combinations with Overtime*

Scenario	***Best***	***2nd Best***	***Diff.***	***Diff %***	***Significance***	***% S.E.***	***No O/T***	***OT% Adv***
1	81.15	77.93	3.22	3.97	99.9	0.085	71.56	13.40
2	88.33	86.41	1.92	2.17	99.9	0.087	77.55	13.90
3	90.66	88.64	2.02	2.23	99.9	0.058	83.60	8.44
4	102.37	100.99	1.38	1.35	99.9	0.083	93.96	8.95
5	71.38	68.32	3.06	4.29	99.9	0.077	64.94	9.92
6	79.37	77.57	1.80	2.27	99.9	0.071	70.27	12.95
7	80.17	77.31	2.86	3.57	99.9	0.059	75.48	6.21
8	92.34	90.34	2.00	2.17	99.9	0.077	84.68	9.05
9	53.83	53.80	0.03	0.06	no	0.083	50.81	5.94
10	57.23	57.10	0.13	0.23	95.0	0.104	57.23	-0.23
11	61.70	60.48	1.22	1.98	99.9	0.103	58.79	4.72
12	67.20	67.12	0.08	0.12	no	0.114	67.20	-0.12
13	50.14	49.70	0.44	0.88	99.9	0.115	47.39	5.80
14	55.09	54.97	0.12	0.22	99.0	0.075	54.44	1.19
15	56.01	55.55	0.46	0.82	99.9	0.072	54.41	2.94
16	64.14	64.10	0.04	0.06	no	0.085	64.10	0.06
Mean	**71.95**	**70.65**	**1.30**	**1.65**	**99.5**	**0.084**	**67.28**	**6.44**
Min			0.03	0.06		0.058	47.39	-0.23

Experimental Conclusions

This experiment shows that using overtime in a job shop can help increase net revenue rate in most scenarios with this model. It also shows that the simplest due date estimation methods (JTW, TWK) and overtime shop floor rules (LOS) perform the best. In most scenarios, the firm should consider flexible overtime when making quotations (policy 3). Overtime in a busy market helps meet orders not just by creating more processing time, but also by enabling the ordinary time of the plant to be used more intensively. This experiment has demonstrated that simulation can help on testing overtime policies with different negotiation strategies and tactics.

Discussion

Organizations are moving slowly along the continuum of e-marketplaces. Most firms use the Internet for communication; many use e-auctions, and a few intelligent agents. However, as yet there has been no real use of automated negotiation in regular business transactions. Further developers and researchers seem to be trying to produce systems that will conduct the negotiations better than people. However, it appears the need is for systems that, although they may not be as good as people at negotiating, can handle the many business transactions that are not negotiated at present due to the cost of negotiating. Organizations will probably never allow an automated negotiation system to handle transactions of major importance to the organization. However, if an automated negotiation system could handle the many less important and semi-routine transactions, then this should lead to decreased supply costs.

The managerial implications are that firms should model their proposed overtime policies and negotiation strategies before implementation, using a model of their expected market and actual firm. This should improve their pricing and delivery time performance in a competitive environment (Li & Lee 1994). This research is a start in exploring how a firm should arrive at and test overtime and negotiation strategies. Easton and Moodie (1999) showed that even very small models can give insight. Like most management software developments, automated negotiation systems will probably come in small increments and take a while to be adopted. Meanwhile, researchers could use simulations to test and develop new systems as demonstrated in this paper.

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