COMPARISON OF LEAD TIME QUOTATION POLICIES IN E-COMMERCE ENVIRONMENT

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ABSTRACT

COMPARISON OF LEAD TIME QUOTATION POLICIES IN E-COMMERCE ENVIRONMENT

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This research is based on problems faced by e-commerce firms while determining lead time for their customers. It is hard to obtain an optimal policy for the tradeoff between serving on-time and quoting short lead times. On-time customer services are positively correlated with rating scores of firms in e-commerce websites. Therefore, in this study, the fluctuation of on-time customer service proportion is used as the main determinant of the rating of the firms and different policies of lead time quotation are compared for managerial insights that can be used in the e-commerce environment. While analyzing policies for the lead time quotation, Semi-Markov Decision Process is used to model the problem and a simulation model is used for demonstrating different scenarios to evaluate lead time quotation policies.

Keywords: Lead time quotation, Reputation level, Tardiness, E-commerce

ÖZ

E-TİCARET ORTAMINDA UYGULANABİLİR TESLİMAT SÜRESİ BELİRLEME POLİTİKALARININ KARŞILAŞTIRILMASI

Altuntaş, Ecem
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Bu araştırma e-ticaret ortamında çalışan firmaların müşterilere teslimat süresi belirlerken karşılaştıkları sorunlara dayanmaktadır. Siparişi önceden belirlenen teslimat süresine uygun göndermek ve müşteriye kısa süreli teslimat süreleri belirlemek arasındaki dengeyi sağlamak adına optimal bir politika bulmak zordur. Bunun yanı sıra, müşterilerin sipariş etme sıklığı e-ticaret sitelerinde verilen puanlamayla pozitif korelasyon içindedir. Bu çalışmada, müşterilerin sipariş etme sıklığındaki dalgalanma ana kısıt olarak kullanılmıştır ve e-ticaret ortamında uygulanabilir farklı teslimat süresi belirleme politikaları karşılaştırılmıştır. Bu politikalar analiz edilirken, senaryoların gösterilmesi için müşterinin alma isteği, sipariş kabul eşiği gibi birçok farklı kısıt içeren bir simülasyon modeli geliştirilmiştir.

Anahtar Kelimeler: Teslimat süresi, Servis, Sipariş, Gecikme, E-ticaret

To my parents who made me go to school on the very first day

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CHAPTER 1

INTRODUCTION

Online selling platforms and e-commerce have been on the scene since eBay is first founded in 1995. It was a great success, many users all around the world became online sellers as they could make money in a fast and easy way. In 2016, it is estimated that around 1.61 billion people used online platforms while they were purchasing goods. Again, in 2016, global e-commerce sales were approximately 1.9 trillion U.S. dollars and it is forecasted that this amount will be 4.06 trillion U.S dollars by 2020. The competition keeps rising among the sellers as potential customer number is increasing every day. However, being a seller is not easy with this high competition in those platforms.

Sellers should consider the reviews they get if they want to increase their revenue which is closely related to the number of customers they attract. 61% of customers read reviews before making any decision about purchasing (Charlton, 2012). Therefore, having positive reviews is more important than before for the sellers using e-commerce sites. Receiving good reviews from customers requires satisfied customers. Customer satisfaction is directly connected with the retention rate of a seller. It increases the likelihood of the customer's returning to the same seller. Retaining customers is defined as "secret weapon" by F. Reichheld and Phil Schefter in their article called "E-loyalty" where they mention economic necessity of gaining a consumer's trust and turning it into loyalty (Reichheld & Schefter, 2000). According to the Bain & Company managers, in the e-commerce environment, profit per customer increases with their life-cycle which is a measure of how often the same customer returns to the same place (Schwager & Meyer, 2007). An article written about electronic commerce discussed that eBay, one of the e-commerce leaders, has the advantages of gaining customers' loyalty. More than 50% of eBay's customers creates a channel for word-of-mouth marketing. The article refers to a study about the repurchasing behavior at leading websites. It is stated that customer's loyalty is determined by quality of customer support, on-time delivery, product presentations, convenient and reasonably priced shipping and transparent privacy policy (Reichheld & Schefter, 2000). As competition increases in e-commerce day by day, there are more choices for a customer who looks for cheaper, faster and better sellers. Therefore, short and reliable lead time quotation is essential for gaining new customers and retaining them.

Gittigidiyor.com, one of the leaders in Turkey e-commerce market, implements a different way about understanding the actual value of on-time orders. After a purchase from any seller in gittigidiyor.com, money is not transferred to seller's account immediately. They wait till the customer receives the order physically and confirms that s/he has got the order through the website. After confirmation, the customer also rates the seller's service. By this method, they track how many orders of a seller are on-time or tardy and obtain information about customer satisfaction.

It is a clear fact that short lead times, on-time delivery and reputation are the basic determinants that affect the purchasing decision of a customer. To keep customers satisfied, quoting short lead times and on-time delivery are both essential, and these two factors significantly affect the arrival rate of customers. However, there is a trade-off between choosing short lead times and serving on-time. Surely, in short term, quoting short lead times would increase the arrival rate. However, as the number of customer orders increases, the quoted lead time must be increased as well. Then, long lead time quotation would attract less customers, so the arrival rate will be decreased.

Sellers may try to keep their customers' arrival rate high, thus quote short lead times without thinking the consequences. When a short lead time is quoted and the demand cannot be met on time, the seller loses the future customers as s/he would not have a good reputation to attract the new ones in the future due to low rating scores. Hence, a seller on an e-commerce site needs to consider both short term and long-term effects of the lead time quote decision. Moreover, if the customer responsiveness is high, the management of lead time decision becomes more significant on the future customer arrival rate.

There are alternative methods in determining a lead time for a customer. One can quote a constant lead time to all customers without any categorization. However, this basic approach has a lot of disadvantages. If demand increases, orders will be delayed. Contrarily, if demand is lower than expected, server utilization decreases, and they miss the opportunity to serve more customers. Alternatively, the seller can categorize the customers according to their priority. In such a case, there would be another tradeoff between allocating the capacity between low-margin and high-margin categories (Keskinocak & Tayur, 2004). One can also quote lead time dynamically and use various variables such as cost of being tardy, customer priority (if applicable), capacity utilization, number of jobs in progress, expected tardiness, service rate, arrival rate of customers.

This thesis aims to analyze the economics of the tradeoff between quoting short lead times and serving the customers on-time. When an e-commerce seller gains customers' trust, i.e. e-loyalty, there will be a positive feedback that will lead to gain new customers. Consequently, as arrival rate of customers increases, it creates a bottleneck or increases missed due dates if there is not enough service capacity. That causes a loss in the number of future customers. Since tardy orders create dissatisfied customers and negative feedback, so the seller loses referrals. In our study, the focus is this cycle of arrival rate fluctuation and how a seller could keep up with it and manage it.

As it is mentioned above, the arrival rate of customers is closely related with the service quality received by the customer. In this thesis, we focus on only the timeliness of the service while considering the service quality. Therefore, the fluctuation of arrival rate is directly related to the reputation levels. In managing the reputation levels if orders are coming with a high rate, seller may consider limiting the future accepted orders. Order acceptance decision is another concern in the scope of due date management and there are many studies in this topic in the literature. One of these studies belong to Duenyas and Hopp (1995). They describe a threshold value for order acceptance and find an optimal value of queue length to reject the orders. In another study, Weng (1996), introduces a model maximizing the profit while categorizing the customers by their sensitivity to lead time lengths. In that study an order acceptance policy for categorized customers is presented by the authors.

In our study, we try to find an insight on how the order acceptance decisions should be given and to what extend it is important for profitability in an environment where meeting the due dates quoted to the recent customers affect the customer arrival rate in the future. The e-commerce environment is chosen to investigate the economic effects of seller reputation in an online channel. Negative/positive feedbacks change the arrival rate of customers and the reputation is a result of the reviews and feedback given by customers. We use these facts to define the reputation level concept in this thesis. Therefore, *reputation level* covers both service performance and arrival rate under one title.

The unethical practice of quoting short lead times while seller anticipates larger lead times is another aspect of the lead time quotation problem which will be investigated in detail in the rest of this study. This would cause losing customers' trust and affects future reputation level.

In this research an M/M/1 queueing system is assumed in an e-commerce environment. The main objective is to understand the structure of the optimal policy for lead time quotation where meeting due dates quoted to current customers affect the future customer arrival rate via reputation levels. The research questions of "what could change with reputation level awareness and how a seller could manage the reputation level fluctuations to increase its profitability" are investigated.

The organization of the rest of this thesis is as follows. In Chapter 2, related works are reviewed. In Chapter 3, we define the problem in detail with the motivation of this research and its methodology. The assumptions about the environment we consider is also mentioned in this chapter. In Chapter 4, the proposed models are introduced. Notations and solution algorithm are given. In Chapter 5, the results of the conducted numerical analysis are reported. In Chapter 6, managerial insights are presented. E-commerce websites are compared in terms of their rating rules and the concepts we use. Finally, in Chapter 7, the conclusion and future work opportunities are presented.

CHAPTER 2

LITERATURE REVIEW

Lead time quotation is a widely studied subject in the literature. One can find considerable amount of research in this area. Many of them are about minimizing the cost of tardy jobs, delay, queue length and maximizing the revenue and earliness. Besides that, there are various constraints.

In most of the studies on due date management, the customer orders are mostly accepted without any limitation and it is assumed that the customers do not accept the quoted lead time if it does not meet their expectations. In many studies, all placed orders are quoted a lead time instantly. After the due dates are determined, the orders are prioritized according to a dispatch policy to optimize the scheduled work. Some of policies used in the studies are First-Come-First-Served (FCFS), shortest/longest processing time, the earliest due date, the earliest operation due date (Duenyas & Hopp, 1995, Duran, 2007, ElHafsi, 2000). However, Keskinocak et al. (2001) consider the lead time sensitivity of the customers and embed it in their proposed models, they determine an acceptable threshold for the order acceptance where the orders exceeding the threshold level are rejected by the customers. Chatterjee et al. (2002) study a profit-maximization model that quotes lead time without using the information of system status. A tardiness penalty for the late deliveries is assumed. They use a log-linear rule for the decision of the lead-time quotations. In another research, Charnsirisakskul et al. (2004) extend the previous studies by price customization and lead time decisions. They assume that the manufacturer has information about the order arrivals and considers a newsvendor policy for ordering. Knowing these parameters, they can schedule the production before the order is placed. They also consider customer preferences for the acceptable latest due date which corresponds to the “threshold limit” for order acceptance in our proposed model.

Spearman and Zhang (1999) study optimal lead time policies in a single class non-preemptive production system. They assume FCFS and formulated two types of problems in the lead time quotation. One of the models quotes the lead times with a serviceability level constraint, i.e. the probability of finishing a job on-time or before the due date, and the other model quotes the lead time with a tardiness level constraint. They find that when a serviceability level is considered, the optimal lead times quoted could be unethical when the system is congested. It is more appropriate to use tardiness level for the optimal lead time quotation. Nonetheless, they point out that, in real life, the second model is hard to implement as it requires unmeasurable parameters like tardiness level and system state probability. So, they apply a constant service policy which requires the minimum amount of information and uses a common reputation level in the market. Also, it gives equivalent results as the optimal tardiness policy.

Oğuz et al. (2010) study simultaneous order acceptance and scheduling decisions in a make-to-order environment. They propose a mathematical model and heuristic algorithms for large sized problems. Their objective is to maximize the total revenue. The model assumes that the tardiness of an order linearly decreases the revenue gained from an accepted order.

In another study by Keskinocak et al. (2013), the computation of expected tardiness of an order at the time of arrival in an M/M/c queuing system is derived. The special case of single server is considered in the paper as well. For a single server system, the expected tardiness is expressed in terms of quoted lead time, the service rate, and the number of jobs in the system at the time of the arrival. This expression is used in our simulation model to estimate the quoted lead time for finding the optimal acceptance policy.

The customer experience has a serious impact on the future business. Therefore, in some of the studies, we see how the service quality is taken into consideration. Some of the researchers assume that the customers may choose another vendor in the next period if the service is not good enough or they evaluate the service accordingly.

Adelman et al. (2013) assume that the number of orders increases with the service quality. In our model, we assume the customers are affected by the past service history, thus the arrival rate of orders changes with the reputation level related to service quality which is measured with the tardiness of the finished jobs.

An empirical analysis is conducted with 15 Italian manufacturers by Zorzini et al. (2007). The study points out due date quotation procedures and capacity planning strategies of the companies. Then, a model is proposed for different type of solutions considering the product and customer properties of the companies. The study mentions an amount of details about the procedures and strategies. According to the analysis made, while quoting due dates, three of the companies do not consider the current workload in the system. From our perspective, the workload of the system has a great impact on quoting an accurate due date.

In a recent study, Nakade and Niwa (2016) consider a system in which the order acceptance depends on the customers' utility functions. Their objective is to find heuristic policies with high profit and customer utilities. Therefore, they compare the optimal policy derived from Markov decision process with different heuristic policies. They conclude that one may prefer other policies rather than the optimal policy with the highest profit. If the decision maker cares more about the customer utility, then heuristic policies could be the better answer as some of these policies result with high utility and competitive profit.

Slotnick (2014) also considers the lead-time quotations when the reputation of the firm is important. In this study, a model is proposed which includes the past actions, i.e. reputation, and the patience of the customer. With a regression analysis and three heuristic solutions, they arrive some conclusions about the correlations between the sensitivity of customers to tardiness reputation and the lead time. In the study, it is suggested that market characteristics should be considered for a better lead time quotation as the market would highly affect the sensitivity of customers. For example, if customers are sensitive to reputation, firm should quote longer lead times to maintain their promises. However, if customers consider the lead times more, then the firm should quote shorter lead times not to lose their current customers, which is considered as an unethical practice in our thesis.

Our study differs from related literature with the concept of unethical quotation. We use unethical quotation as a choice of the firm while trying to analyze whether practicing unethical quotation bring additional profit or not. The simulation model, which is given in the next chapters, proposes a numerical analysis of the trade-off between generating profit and customer satisfaction. We try different scenarios with different parameters while performing the numerical analysis. The results we get from the analysis are presented as business insights. By our analysis, we try to contribute to literature with business related insights explained in Chapter 6, that compare some real-life examples.

CHAPTER 3

PROBLEM ANALYSIS

This chapter discusses the preliminaries on the research problem and the explanation of it along with the assumptions.

One of the most common problems encountered in a make-to-order system is the due date management. The decisions given about the lead time quotation and the order acceptance are crucial for the success of the business. As mentioned previously, quoted due date is the key aspect for the customers while they choose a seller or a manufacturer to order a product or service. After customer places an order, the firm quotes her a lead time. If the service completion time or the product delivery time exceeds the given lead time, undesired consequences may emerge such as monetary penalties and potential loss of the future customers. Therefore, rejecting some of the orders may be considered according to an acceptance policy in order to not lose the future potential customers. On the other hand, the seller can quote shorter lead times to maintain current customers and increase the net profit in the short run, despite the negative reputation that may be gained in the future. It is not trivial to decide which lead time quotation behavior would be more advantageous for the firm.

The monetary penalty mostly considered in the literature increases with the tardiness of the order (Hafızoğlu, Gel, & Keskinocak, 2013). The tardiness is defined as the difference between the completion time of the order and the promised due date, if completion time is later than the due date, otherwise it is equal to zero.

If the firm implements a strategy considering long term effects, the lead time is quoted based on some estimation and forecast of the arrival rate of the customers. The ability to estimate the expected tardiness of an order and use this estimate for lead time decisions certainly decrease the negative impacts and penalties of late orders.

Therefore, the expected tardiness must be primarily considered in the lead time management (Hafızoğlu et al., 2013).

In quoting the lead time, companies should consider the tradeoff between quoting short lead times and meeting the lead times on time. While deciding how to manage the lead time quotations, the fact that the arrival rate of the customers is closely related with the customer satisfaction and previous experience should be considered. In this study, we limit the previous experience of the customer to whether the customer has received his order on-time or not. If the order is on-time, this would bring a positive impact on the future customer arrival rate.

While considering a make-to-order system, we mainly focus on the e-commerce environment in this study. The simulation model we utilize may give some business insights for e-commerce sellers. As the competition keeps growing in this area, the trade-off between risk mitigation and risk acceptance becomes more crucial. The most important risk a seller might face in an e-commerce environment is the policy adopted under different conditions. There are rating procedures like scores, reviews, etc. in the e-commerce platforms to give the customers more information about the seller or the product. Therefore, a seller on such a platform should be aware of the effects of the ratings/reviews and how these are perceived by the potential customers. A survey study conducted on some of the e-commerce websites shows us that high ratings result in higher perception of product quality and purchasing intention (Flanagin et al., 2014).

Another issue that should be discussed is the quotation of short lead times. Implementing short lead time quotation policy is an unethical practice from the business ethics perspective. In this thesis we consider the effect of unethical lead time quotation on the profits via the arrival rate of customers.

If the reputation of a firm is positively correlated with the arrival rate of customers and the firm finds an effective policy for lead time quotation based on different reputation scores, then increasing rate of customer arrivals can generate higher profits.

For example, if a new firm with low reputation might have less customers coming in, intuitively the firm needs to finish more orders on-time, which require limited or no unethical quotation.

The problem of lead time quotation when the past performance of meeting the quoted lead time affects the future arrival of customers is modeled in the next chapter. The assumptions and proposed models are formulated and explained in further details.

CHAPTER 4

PROPOSED MODEL

We consider the problem under a single-server queueing system in First-Come-First-Served (FCFS) basis. Customers arrive to the system according to a stochastic process with an arrival rate (λ) where $\lambda > 0$. The arrival rate of customers is a function of the reputation level of the seller at that moment and the reputation level changes with the seller's service performance. Customers arrive to the seller and they are accepted or rejected by the seller's decision of quoting a lead time smaller than a predetermined maximum acceptable lead time by customers or not. The server has a service time distribution with cumulative distribution function F. When the seller completes the service, the reputation level of the seller increases or decreases according to being on-time or tardy. The arrival rate of new customers depends on the reputation level of the seller at the time of a new arrival. The process flow mentioned above is illustrated in Figure 4.1.

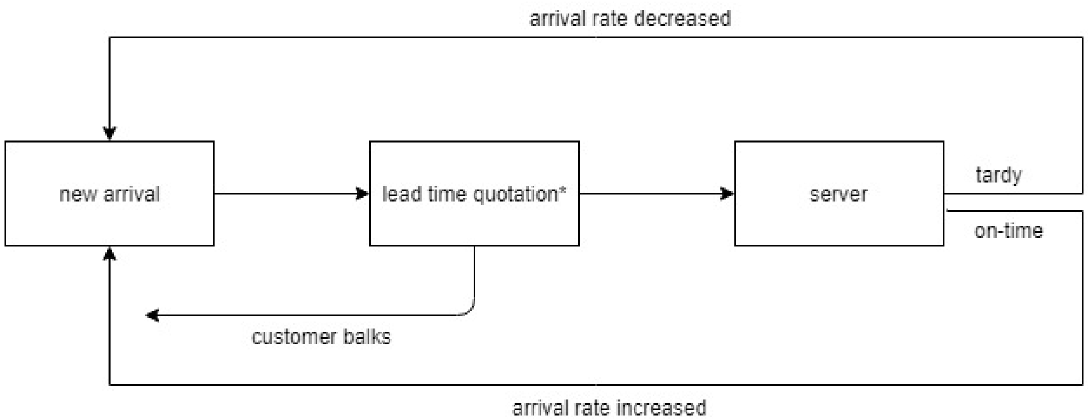

Figure 4.1. Process flow under consideration (can be unethical)*

The problem on-hand can be modeled as a Semi Markov Decision Process (SMDP) as the past service performance of the seller effects the future potential customers which means our future state is not independent of the past. Also, we consider the arrival times of customers as our decision epochs, so system state changes with a random amount of time. In order to formulate the problem, we need to keep track of the number of orders in the system, reputation level and the time left until the quoted lead time (L_Q) for each order that enters to the system.

The accepted orders create an immediate revenue of R, and if the seller cannot deliver the orders on-time (within the quoted lead time) then the seller pays a penalty, c, per unit time. So, the state of the system is defined as $(rl, u, n, t_1, \dots, t_i, t_{i+1}, \dots, t_{n+i})$ where *rl* is the reputation level at the time of a new customer arrival, i.e. $(n+i+1)^{th}$ customer to the system. Reputation level, *rl*, changes with the completion time of the customers. When the service is completed on-time, i.e. within the quoted lead time, *rl* is affected positively, otherwise it has a counter effect. To continue with the other variables, u is the service time spent on the current job in the server, n is the number of jobs still not finished, i is the number of completed jobs, t_j is the time left until the due date quoted to accepted customer j which ranges between $(-\infty, L_Q^j]$. The negative values for t_j indicates the amount of tardiness for the accepted order, j.

Let g^* denote the optimal average profit per arrival and $v(rl, u, n, t_1, \dots, t_{n+i})$ denote the relative value function. $w(rl, u, n, t_1, \dots, t_{n+i-1})$ represents the expected profit after the decision of $(n+i)^{th}$ accepted order is given. Thus, the SMDP recursion would be as the following:

$$g^* + v(rl, u, n-1, t_1, \dots, t_{n+i-1}) = max \left\{ \begin{matrix} R - C_{n+i}(u) + w\left(rl, u, n, t_1, \dots, t_{n+i} = L_Q^{n+i}(rl, n)\right), \\ w(rl, u, n-1, t_1, \dots, t_{n+i-1}) \end{matrix} \right\}$$

where

$$C_{i+n}(u) = \int_{L_Q^{i+n}(rl,n)}^{\infty} c(x - L_Q^{i+n}(rl, n)) dF_{i+n}^{u}(x) .$$

$F_{i+n}^{u}(x)$ equals to the convolution between F^{u} and F_{i+n-1}. F^{u} is the probability distribution function of service time of an order which has been in service for *u* time. F_{i+n-1} is the $(n+i-1)$-fold convolution of *F*, the probability distribution of service time. $L_{Q}^{i+n}(rl,n)$ is the lead time quoted to customer $(n+i)$ when there are *n* customers not served yet in the system and reputation level is *rl* at its arrival. So, $C_{i+n}(u)$ formulates the expected tardiness cost of $(n+i)^{th}$ accepted order to the system and first order has already been in service for *u* time.

The joint conditional probability of completing exactly *k* orders during the interarrival time γ with probability density function $h^{rl}(\gamma)$ is defined as $Q_{u,t_1,\ldots,t_{i+k}}^{\gamma,m}(k,\tau)$. The first *m* orders of the finished *k* orders completed on or before their due dates $(m \leq k)$ and have the $(k+1)^{th}$ customer in service for τ time or less. X_j is the service time for the j^{th} order.

$$Q_{u,t_1,\ldots,t_{i+k}}^{\gamma,m}(k,\tau) = P\left\{\sum_{j=1}^{k} X_j \leq \gamma + u, \sum_{j=1}^{k+1} X_j > \gamma + u, \gamma + u - \sum_{j=1}^{k} X_j \leq \tau, t_1 \geq 0, \ldots, t_m \geq 0, \right.$$

$$\left. \sum_{j=1}^{b} X_j - u \leq t_b, b = 1, \ldots, m \mid X_1 > u \right\}$$

The expected profit, $w(rl,u,n,t_1,\ldots,t_{i+n})$ is defined as following;

$$w(rl,u,n,t_1,\ldots,t_i,t_{i+1},\ldots,t_{i+n}) = \int_{\gamma=0}^{\infty} h^{rl}(\gamma)\left[\sum_{k=0}^{n-1}\sum_{m=0}^{k}\int_{\tau=0}^{\infty} v(rl,\tau,n-k,t_1,\ldots,t_i,t_{i+1}-\gamma,\ldots,t_{i+n}-\gamma)\right.$$

$$\left. dQ_{u,t_1,\ldots,t_i,t_{i+1},\ldots,t_{i+k}}^{\gamma,m}(k,\tau) + \sum_{k=n}^{\infty}\sum_{m=0}^{k}\int_{\tau=0}^{\infty} v(rl,0)\, dQ_{u,t_1,\ldots,t_i,t_{i+1},\ldots,t_{i+k}}^{\gamma,m}(k,\tau)\right]$$

Reputation levels are calculated in three different ways in this study. In the first case the reputation level is increased/decreased at every service completion according to its good/poor performance. In the second case the reputation level is increased/decreased according to a Bernoulli decision with a success probability of *p* and failure probability, q. So, with a probability of *p*, the reputation level increases and with a probability of q, reputation level decreases. In the third case the reputation level is calculated according to the average reputation levels of the previous orders.

When m jobs out of k $(\leq i)$ are finished on-time during the interarrival for the first case the reputation level at the time of a new order arrival is defined as;

$$(rl + 2m - k)^{+} = \max(0, rl + m - (k - m)).$$

For the second case the reputation level at the time of a new order arrival is defined as;

$$(rl + (p + q)m - qk)^{+} = \max(0, rl + pm - q(k - m)).$$

For the third case the reputation level at the time of a new order arrival is defined as;

$$\left\lfloor \frac{i.rl + (2m - i)^{+}}{k + i} \right\rfloor.$$

The quoted lead time is a function of both the reputation level (rl) and number of orders in the system (n). To define $L_Q^{i+n}(rl, n)$, we first need to define other variables, maximum acceptable lead time (L_{max}) and expected completion time according to the current system state (T_E^n). In the system, it is assumed that all customers have a common maximum acceptable lead time (L_{max}). In other words, if the customer is quoted more than L_{max}, s/he does not place the order.

For each customer arrival, an expected tardiness is considered first by utilizing the expected tardiness formula ($ETA_n(d)$) given by Hafızoğlu et al. (2013). Using this formula, when there is a single server in the system, to compute the expected tardiness, service rate (μ), base lead time (d), and the number of orders in the system (n) upon arrival of the new order are required.

$$ETA_n(d) = \frac{e^{-d\mu}}{\mu} \sum_{i=0}^{\mathrm{n}} (d\mu)^{i} \frac{\mathrm{n} + 1 - i}{i!}$$

Calculated expected tardiness for each arrival is then added on top of the base lead time (d) to determine the expected completion time. Therefore, for an arriving customer to a system which has n customers not served yet, the expected completion time is calculated as follows:

$$T_E^n = ETA_n(d) + d \tag{4.1}$$

Then, we can define $L_Q^{i+n}(rl, n)$ as the minimum of L_{max} and T_E^n. This is the lead time quotation policy of the seller which represents another problem discussed in previous chapter as unethical lead time quotation.

$$L_Q^{i+n}(rl, n) = \min\{L_{max}, T_E^n\} \tag{4.2}$$

Unfortunately, the state space of the formulated SMDP above is infinite since we need to keep track of the left-over time for each customer accepted to the system. This makes it impossible to find the optimal lead time satisfying the conditions above. Therefore, a simulation model is used as a tool to evaluate policies for lead time quotation.

CHAPTER 5

NUMERICAL ANALYSIS

To evaluate the performance of different lead time quotation policies, a simulation model is developed using MATLAB, and details are discussed in this section. To evaluate different lead time quotation policies, the average profit per customers are compared.

The lead time is quoted immediately when the order comes into the system. There is a threshold limit which is a constraint for quoted lead time. In other words, if the quoted lead time is less than the threshold level, the order is placed by the customer. Otherwise, the customer leaves the system without placing an order. The threshold levels give an insight to the firm about the trade-off between quoting short due dates and meeting the orders on time. For example, when the reputation level is very high and there are many customers in the system, the seller may offer lead times that are accepted by customer even he knows he might not be able to meet those lead times which is referred as "*unethical quotation*". When $L_{max} < T_E^n$, if the seller offers a lead time of L_{max}, it is considered as *an unethical quoting*. Seller expects the completion time to be longer than L_{max} but offers L_{max} to get the order. On-time service completions increase the reputation level and more customers enter the system in the future. As the reputation level increases, the management might want to take the risk and accept more customers even if this means accepting customers with unethical quotation while the system is congested. This could create some additional profit capture for the firm.

With the proposed simulation model, we search for an insight about policies for lead time quotation. For understanding the effects of unethical quoting, we vary the quoted lead times for the arrived customers in an unethical way. If the expected completion time is higher than the customer's acceptance threshold limit, we quote the minimum lead time value that the customer would accept which is obviously shorter than the previous one. Therefore, the customer would enter the system. By checking how much the revenue changes, we can evaluate whether unethical quotation is beneficial or not.

As it is mentioned previously, an M/M/1 queuing system with FCFS policy is assumed. Namely, arrival rate, $\lambda(rl)$, is a function of the recent reputation level (*rl*). Arrival rates have constant *lower* (LL_r) and an *upper* (UL_r) bounds decided according to the previous experience. The seller also decides how many reputation levels it has. In the numerical experiments, arrival rates are taken as discrete numbers that are distributed in the specified range [LL_r, UL_r]. Arrival rate is increased or decreased by equal amounts within the specified range. For example, if there are three reputation levels, and [LL_r, UL_r] = [7, 7.72], then the set of arrival rates would be $\{7, 7.36, 7.72\}$

Namely, the arrival rates corresponding to the three reputation levels would be:

$$\lambda\,(rl = 1) = 7, \qquad \lambda\,(rl = 2) = 7.36\ and\ \lambda\,(rl = 3) = 7.72$$

The decision of quoted lead time is controlled with an additional acceptance threshold function which has a value for each different reputation level. We control the order acceptance by determining an upper bound for a given reputation level (*rl*). If the calculated expected completion times (T_E) are lower than the specified threshold, then the customer is accepted. However, if the calculated expected completion time is more than the determined threshold, a longer lead time is quoted and the customer balks. By using limited order acceptance, we try to understand the business implications of reputation level shifts and threshold patterns.

The function of acceptance threshold lead time for a system with three reputation levels could be as following;

$$L_{TH}(\,rl) = \left\{\frac{4}{\mu}\ for\ rl = 1,\ \frac{5}{\mu}\ for\ rl = 2,\ \frac{6}{\mu}\ for\ rl = 3\right\}.$$

The input data for the simulation are the random interarrival times and service times. Different distribution functions (exponential, uniform and normal) are utilized. Service time is a random variable with mean $1/\mu$, where μ is the service rate.

Interarrival time is a random variable with mean $1/\lambda$, where λ is the arrival rate. The random variates are generated by utilizing Inverse Transform Technique for the exponential and uniform distribution cases.

For the exponential distribution, the random variable for service time (X_i) and interarrival time (Y_i) for order i is found by;

$$X_i = -\frac{1}{\mu} lnU_i$$

$$Y_i = -\frac{1}{\lambda} lnU_i$$

where U_i is a uniform random variable over the interval (0,1).

For the uniform distribution, the random variable for the service time (X_i) and interarrival time (Y_i) which are distributed on the interval [a, b], is found by;

$X_i = a + (b - a)U_i$ and $Y_i = a + (b - a)U_i$.

For normal distribution, inverse transform technique cannot be used because the inverse of normal distribution does not have a closed form. Therefore, random variate generator of simulation tool is used for normal distribution case.

Then T_E^k is calculated for the arrival k as in Formula 4.1 and L_Q is determined as in Formula 4.2. However, we limit the L_Q with the $L_{TH}(rl)$ as follows.

$$L_Q^k(rl, n) = \begin{Bmatrix} \min\{L_{max}, T_E^k\}, & T_E^k \leq L_{TH}(rl) \\ \infty \quad , & otherwise \end{Bmatrix}$$

The output data of the simulation model is the profit per arrival which is the performance measure of different lead time quotation policies to evaluate. Additionally, the number of unethical lead times quoted is also observed to discuss the effectiveness of selected policies.

With the proposed simulation model, we try to identify how the firm could manage its due date quotation and investigate if it is worthy to use unethical quotation or not. By finding an appropriate lead time policy for the customer acceptance, a firm can increase its profit.

We present the notations used for the proposed simulation model in Table 4.1 below.

Table 5.1. *Notations used for simulation models*

λ_k	Arrival rate for the k^{th} arrived customer
$[LL_r, UL_r]$	Interval of arrival rates
μ	Service rate
rl	Reputation level
$L_{TH}(rl)$	Acceptance threshold lead time at reputation level rl
T_E^k	Expected completion time of k^{th} arrival
L_Q^k	Quoted lead time of k^{th} arrival
L_{max}	Maximal value that should be quoted to ensure acceptance by customer
ETA_k	Expected tardiness of k^{th} arrival
R	Revenue per customer
c	cost per time
g_k	Average profit per customer
d	Base lead time used in the ETA_k formula

The numerical analysis is conducted based on three reputation level calculation methods mentioned in Chapter 4. The first part represents a benchmark for the other ones. In the first one, the *quoted lead time* (L_Q^k) is constant. Then, it is extended with *dynamic lead time with unethical* quoting options.

This chapter is organized as following. In Section 5.1, the results of constant lead time quotation with different parameters are presented. Different reputation level calculations and arrival rate intervals are considered. Different distributions are used for the input variables. The results are grouped according to the types of reputation level calculations. Constant lead time quotation cases serve as a benchmark for our study to understand whether using dynamic lead time quotation make sense or not. In Section 5.2, dynamic lead time quotation results are presented. L_{TH} values are analyzed according to different cases.

As it is mentioned in the Chapter 4, there are three cases used for reputation level calculations. In the following sections, first case is referred as *Basic case,* second one is referred as *Bernoulli case* and the third case is referred as *Average case*.

Different distributions are used for service times and interarrival times for further analysis. Exponential, uniform and normal distributions are used. For exponential distribution, service time has a mean of $1/\mu$ and arrival time mean varies between $[1/LL_r,\ 1/UL_r]$. For normal distribution, service time has parameters $(1/\mu\,, \sigma_s)$ and arrival time has $(1/\lambda\,, \sigma_a)$. For uniform distribution, service time is distributed between $[0, 2/\mu,]$ and arrival time is distributed between $[0, 2/\lambda]$.

The 95% confidence intervals for average profit per arrival are calculated as following by utilizing z-score from standard normal distribution as the sample size is large enough.

$$\bar{X}\ \pm z_{1-\alpha/2}\frac{\sigma}{\sqrt{n}}$$

Normality assumption is checked for the best case in Table 5.22. First, QQ plot is used as a visualization technique which is represented in Figure 5.1. Additionally, Lilliefors test is used as a hypothesis testing for goodness-of-fit. Lilliefors test fails to reject the null hypothesis, namely the claim that the data comes from a normal distribution, with *p-value* > 0.05. Lilliefors test is chosen since it is valid for the data with unknown mean and standard deviation of population and estimates these parameters from the sample data.

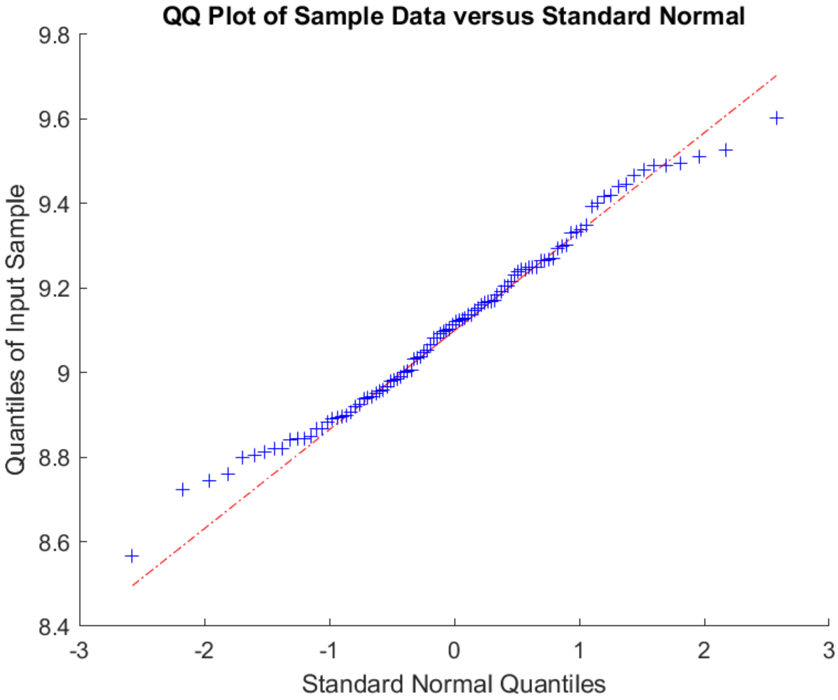

Figure 5.1. QQ plot of the best case shown in Table 5.22

After determining the confidence interval for each lead time quotation policy, these policies are ranked according to their average profit per arrival. Then first ten policies with confidence intervals that are not overlapping are selected. The results are presented in the following sections.

Given the parameters μ, $[LL_r, UL_r]$, L_{TH}, R, c, L_{max} and *base lead time (d)* for expected tardiness calculations, we create a single server queueing system. We calculate the performance indicators for i=1,000 served customers with 100 replications and confidence intervals for average profit per arrival are calculated.

5.1. Constant Lead Time Quotation

5.1.1. Basic Case

Firstly, a simple model, where a *constant* lead time is quoted independent of the orders, reputation level and tardiness, is considered. No unethical quotation is allowed. The parameters used are represented in Table 5.1. The observations which are the average profit per arrival and 95% confidence intervals are shown in Table 5.2.

Exponential, uniform and normal distributions are used for input variables, i.e. arrival and service times.

Table 5.2. *Parameters for Constant Lead Time Model – Basic Case*

Parameters	
μ	8
[LL_r, UL_r]	[7, 7.72]
# of rl	5
R	10
c	10
σ_a	0.15
σ_s	0.1

Table 5.3. *Average profit and 95% confidence intervals for profit generated per arrival for the three distributions with parameters shown in Table 5.1.*

L_Q	*Exponential*		*Uniform*		*Normal*	
$1/\mu$	2.14	[1.4, 2.87]	7.18	[7.01, 7.35]	2.30	[1.70, 2.90]
$2/\mu$	2.89	[2.04, 3.75]	8.11	[7.97, 8.24]	3.43	[2.71, 4.15]
$3/\mu$	3.95	[3.39, 4.5]	8.46	[8.36, 8.57]	3.96	[3.41, 4.50]
$4/\mu$	4.62	[4.03, 5.2]	8.86	[8.74, 8.98]	4.72	[4.21, 5.23]
$5/\mu$	5.05	[4.51, 5.6]	9.08	[8.97, 9.20]	5.31	[4.81, 5.81]
$6/\mu$	5.45	[4.95, 5.95]	9.25	[9.16, 9.34]	5.67	[5.06, 6.29]
$7/\mu$	6.11	[5.56, 6.65]	9.31	[9.21, 9.41]	6.21	[5.70, 6.71]

Table 5.2. shows the results of constant lead time quotation with different values for L_Q^k. Exponential, uniform and normal distributions are used for the input variables service time and interarrival time. As the results show, average profit per arrival varies between [2.14, 6.11] for exponential, [7.18, 9.31] for uniform and [2.30, 6.21] for normal distribution.

In Tables 5.3 and 5.4, the results of narrowed down and expanded arrival rate intervals are presented.

Table 5.4. *Average profit and 95% confidence intervals for profit generated per arrival for the three distributions with parameters shown in Table 5.1 with [LLr, ULr] = [4,5]*

L_Q	*Exponential*		*Uniform*		*Normal*	
$1/\mu$	8.45	[8.4, 8.49]	9.38	[9.37, 9.39]	9.09	[9.07, 9.11]
$2/\mu$	8.96	[8.92, 9]	9.81	[9.8, 9.81]	9.51	[9.49, 9.53]
$3/\mu$	9.31	[9.27, 9.35]	9.94	[9.93, 9.94]	9.72	[9.71, 9.73]
$4/\mu$	9.57	[9.54, 9.59]	9.98	[9.97, 9.98]	9.84	[9.83, 9.85]
$5/\mu$	9.71	[9.68, 9.73]	9.99	[9.98, 10]	9.92	[9.91, 9.93]
$6/\mu$	9.81	[9.78, 9.83]	9.99	[9.98, 10]	9.95	[9.94, 9.96]
$7/\mu$	9.85	[9.82, 9.87]	9.99	[9.98, 10]	9.97	[9.96, 9.98]

According to the results shown in Table 5.3, when the arrival rate interval is narrowed down to [4, 5], a dramatic increase in profit is observed.

Table 5.5. *Average profit and 95% confidence intervals for profit generated per arrival for the three distributions with parameters shown in Table 5.1 with [LLr, ULr] = [4,7.72]*

L_Q	*Exponential*		*Uniform*		*Normal*	
$1/\mu$	8.30	[8.25, 8.35]	9.32	[9.31, 9.33]	8.95	[8.93, 8.97]
$2/\mu$	8.71	[8.67, 8.75]	9.62	[9.61, 9.63]	9.12	[9.09, 9.15]
$3/\mu$	9.02	[8.97, 9.07]	9.77	[9.75, 9.79]	9.30	[9.27, 9.33]
$4/\mu$	9.21	[9.16, 9.26]	9.84	[9.83, 9.85]	9.44	[9.41, 9.45]
$5/\mu$	9.37	[9.33, 9.41]	9.89	[9.88, 9.89]	9.55	[9.53, 9.57]
$6/\mu$	9.48	[9.45, 9.51]	9.91	[9.9, 9.92]	9.63	[9.61, 9.65]
$7/\mu$	9.55	[9.52, 9.58]	9.93	[9.92, 9.94]	9.67	[9.65, 9.69]

5.1.2. Bernoulli case

As introduced in the previous chapters, Bernoulli case is when the reputation levels are increased or decreased according to a success probability, p and failure probability, q. The parameters used for calculations are shown in Table 5.4.

Table 5.6. *Parameters for Constant Lead Time Model – Bernoulli Case*

Parameters	
μ	8
$[LL_r, UL_r]$	[7, 7.72]
# of rl	5
R	10
c	10
p	0.2
q	0.6
σ_a	0.15
σ_s	0.1

Table 5.7. *Average profit and 95% confidence intervals for profit generated per arrival for the three distributions with parameters shown in Table 5.4.*

L_Q	*Exponential*		*Uniform*		*Normal*	
$1/\mu$	1.06	[0.39, 1.73]	7.08	[6.87, 7.29]	2.36	[1.84, 2.87]
$2/\mu$	2.93	[2.27, 3.57]	8.10	[7.93, 8.26]	3.28	[2.71, 3.83]
$3/\mu$	3.95	[3.28, 4.62]	8.52	[8.37, 8.66]	4.09	[3.43, 4.73]
$4/\mu$	4.28	[3.63, 4.92]	8.71	[8.56, 8.85]	4.26	[3.71, 4.8]
$5/\mu$	5.23	[4.7, 5.76]	9.11	[8.98, 9.23]	5.26	[4.75, 5.77]
$6/\mu$	4.70	[3.78, 5.61]	9.29	[9.18, 9.38]	5.43	[4.87, 5.98]
$7/\mu$	5.65	[5.04, 6.24]	9.34	[9.22, 9.45]	5.88	[5.23, 6.52]

When reputation level is changed according to a Bernoulli trial, average profit per arrival is similar to the results found in Table 5.2. In Tables 5.6 and 5.7, the results of narrowed down and expanded arrival rate intervals are presented.

Table 5.8. Average profit and 95% confidence intervals for profit generated per arrival for the three distributions with parameters shown in Table 5.4 with [LLr, ULr] = [4,5]

L_Q	*Exponential*		*Uniform*		*Normal*	
$1/\mu$	8.46	[8.41, 8.51]	9.39	[9.38, 9.4]	9.14	[9.12, 9.15]
$2/\mu$	8.99	[8.94, 9.03]	9.81	[9.8, 9.82]	9.59	[9.57, 9.6]
$3/\mu$	9.37	[9.33, 9.39]	9.93	[9.92, 9.94]	9.75	[9.73, 9.75]
$4/\mu$	9.54	[9.51, 9.57]	9.98	[9.97, 9.99]	9.84	[9.83, 9.85]
$5/\mu$	9.69	[9.66, 9.71]	9.99	[9.98, 10]	9.92	[9.91, 9.93]
$6/\mu$	9.79	[9.76, 9.81]	9.99	[9.98, 10]	9.96	[9.95, 9.97]
$7/\mu$	9.87	[9.85, 9.88]	9.99	[9.98, 10]	9.97	[9.96, 9.98]

The results shown in Table 5.6 are similar to the basic case introduced in Table 5.3.

Table 5.9. *Average profit and 95% confidence intervals for profit generated per arrival for the three distributions with parameters shown in Table 5.4 with [LLr, ULr] = [4,7.72]*

L_Q	*Exponential*		*Uniform*		*Normal*	
$1/\mu$	8.42	[8.37, 8.47]	9.38	[9.37, 9.39]	9.11	[9.09, 9.13]
$2/\mu$	8.91	[8.87, 8.95]	9.68	[9.67, 9.69]	9.36	[9.34, 9.38]
$3/\mu$	9.12	[9.08, 9.16]	9.77	[9.76, 9.78]	9.42	[9.39, 9.45]
$4/\mu$	9.27	[9.24, 9.3]	9.83	[9.82, 9.84]	9.48	[9.46, 9.5]
$5/\mu$	9.36	[9.32, 9.4]	9.89	[9.87, 9.91]	9.56	[9.54, 9.58]
$6/\mu$	9.50	[9.46, 9.54]	9.91	[9.89, 9.93]	9.62	[9.59, 9.65]
$7/\mu$	9.56	[9.53, 9.59]	9.93	[9.92, 9.94]	9.67	[9.65, 9.69]

5.1.3. Average Case

In this section, reputation level for the next arrival is the average of the past reputation levels. The parameters are introduced in Table 5.7.

Table 5.10. *Parameters for Constant Lead Time Model – Average Case*

Parameters	
μ	8
$[LL_r, UL_r]$	[7, 7.72]
# of rl	5
R	10
c	10
σ_a	0.15
σ_s	0.1

Table 5.11. *Average profit and 95% confidence intervals for profit generated per arrival for the three distributions with parameters shown in Table 5.7.*

L_Q	*Exponential*		*Uniform*		*Normal*	
$1/\mu$	0.29	[-0.5, 1.08]	6.69	[6.48, 6.89]	1.75	[0.98, 2.52]
$2/\mu$	-1.18	[-2.72, 0.35]	6.22	[5.73, 6.7]	0.74	[-0.2, 1.69]
$3/\mu$	-1.25	[-2.67, 0.18]	5.70	[5.22, 6.16]	-0.27	[-1.52, 0.98]
$4/\mu$	-0.12	[-1.41, 1.17]	5.79	[5.12, 6.46]	1.44	[0.32, 2.56]
$5/\mu$	-0.20	[-1.65, 1.24]	6.58	[6.02, 7.14]	0.89	[-0.22, 1.99]
$6/\mu$	0.08	[-1.32, 1.47]	6.79	[6.29, 7.28]	-2.02	[-3.86, -0.18]
$7/\mu$	0.59	[-0.79, 1.97]	6.84	[6.22, 7.45]	0.12	[-1.44, 1.67]

When reputation level is calculated according to average of past reputation levels, average profit per arrival decreases and varies in the interval [-1.25, 0.59] for exponential, [5.7, 6.84] for uniform and [-2.02, 1.75] for normal distribution which are much lower from the previous cases. In Tables 5.9 and 5.10, the results of narrowed down and expanded arrival rate intervals are presented.

Table 5.12. *Average profit and 95% confidence intervals for profit generated per arrival for the three distributions with parameters shown in Table 5.7 with [LLr, ULr] = [4,5]*

L_Q	*Exponential*		*Uniform*		*Normal*	
$1/\mu$	8.04	[7.97, 8.1]	9.25	[9.23, 9.26]	8.77	[8.74, 8.8]
$2/\mu$	8.56	[8.48, 8.62]	9.74	[9.72, 9.75]	9.23	[9.2, 9.26]
$3/\mu$	8.98	[8.91, 9.03]	9.91	[9.9, 9.92]	9.52	[9.49, 9.55]
$4/\mu$	9.22	[9.15, 9.28]	9.97	[9.96, 9.98]	9.74	[9.71, 9.76]
$5/\mu$	9.50	[9.44, 9.54]	9.98	[9.97, 9.99]	9.85	[9.82, 9.87]
$6/\mu$	9.67	[9.62, 9.72]	9.99	[9.98, 10]	9.92	[9.91, 9.93]
$7/\mu$	9.74	[9.7, 9.77]	9.99	[9.98, 10]	9.96	[9.94, 9.97]

Table 5.13 *Average profit and 95% confidence intervals for profit generated per arrival for the three distributions with parameters shown in Table 5.7 with [LLr, ULr] = [4,7.72]*

L_Q	*Exponential*		*Uniform*		*Normal*	
$1/\mu$	6.93	[6.77, 7.09]	8.30	[8.23, 8.37]	7.76	[7.66, 7.86]
$2/\mu$	6.50	[6.28, 6.7]	7.45	[7.28, 7.62]	7.17	[6.94, 7.38]
$3/\mu$	5.85	[5.35, 6.35]	7.53	[7.34, 7.71]	6.86	[6.65, 7.07]
$4/\mu$	5.57	[5.03, 6.09]	7.51	[7.24, 7.77]	6.63	[6.19, 7.05]
$5/\mu$	6.04	[5.65, 6.42]	7.43	[7.15, 7.7]	6.56	[6.11, 7.01]
$6/\mu$	5.68	[5.08, 6.26]	6.69	[6.13, 7.24]	6.24	[5.67, 6.81]
$7/\mu$	5.42	[4.79, 6.03]	6.61	[6.16, 7.05]	6.27	[5.85, 6.69]

Narrowing down the arrival rate interval increases the profit in all of three cases introduced above. However, constant lead time quotation policy has many drawbacks that a seller should consider. Quoting constant lead time for each customer is unrealistic because there are many other parameters in real life like willingness to pay of a customer and likelihood of waiting the order. In fact, it is expected to observe high profits in the results above when there are low arrival rates and long quoted lead times. Our cost measure is just tardiness in the study, so, because of quoting larger lead times when there are not many arrivals in the system, there are not any cost to decrease profit. However, in real life cost measures can vary according to different environments.

Also, there are many assumptions while applying constant lead time quotation policy. We assume that future arrivals are not affected by past performance like there is not any other competition in the market which is not the case in real life for many situations.

To conclude, when there are high arrival rates, constant lead time quotation policy does not bring high profits. However, if the arrivals are low, the additional profit is not realistic as a customer willingness to wait would not be that high. Therefore, another policy is introduced in Section 5.2 which considers past performance, current jobs on hand, willingness to wait of a customer.

5.2. Dynamic Lead Time Quotation

After the benchmark results are obtained, the model is extended a step further with *expected tardiness* and *unethical quotation*. In this case, the *quoted lead time* (L_Q^k) becomes a function of the number of orders waiting in the queue and the *service time*. Each arrival is quoted a lead time considering the past performance of the system.

Expected tardiness in a single server queueing system is calculated with three parameters: *service rate*, *orders in the queue* and *quoted lead time.* The planned completion time is calculated considering the *expected tardiness* given *the base lead time (d)* is equal to 1/μ.

Basic case, Bernoulli case and average case for reputation level calculations with dynamic lead time quotation is presented in the following sub-sections.

5.2.1. Basic Case

The parameter values are given in Table 5.10. Table 5.11 and 5.12 show the results when exponential, uniform distributions are used respectively.

Table 5.14. *Parameters for Dynamic Lead Time Model – Basic Case*

Parameters	
μ	8
$[LL_r, UL_r]$	[7, 7.72]
# of rl	5
L_{max}	4/μ
L_{TH}	{4/μ, 5/μ, 6/μ, 7/μ}
d	1/μ
R	10
c	10

Table 5.15. *First ten policies with basic case – exponentially distributed service & arrival time*

Lead Time Quotation Policy							
L_{TH} *(1)*	L_{TH} *(2)*	L_{TH} *(3)*	L_{TH} *(4)*	L_{TH} *(5)*	*Average Unethical Quotation*	*Average Profit per arrival*	*Confidence Interval*
4/μ	4/μ	7/μ	7/μ	5/μ	84	9.4290	[9.42, 9.44]
4/μ	4/μ	5/μ	7/μ	6/μ	69	9.4090	[9.39, 9.41]
4/μ	4/μ	6/μ	6/μ	7/μ	104	9.3860	[9.37, 9.39]
4/μ	6/μ	5/μ	4/μ	4/μ	51	9.3664	[9.35, 9.37]
5/μ	4/μ	6/μ	4/μ	7/μ	104	9.3483	[9.33, 9.35]
5/μ	7/μ	6/μ	5/μ	6/μ	225	9.3264	[9.31, 9.33]
6/μ	4/μ	4/μ	4/μ	6/μ	92	9.3051	[9.29, 9.31]
6/μ	6/μ	4/μ	4/μ	4/μ	50	9.2796	[9.26, 9.29]
6/μ	7/μ	4/μ	4/μ	5/μ	165	9.2521	[9.23, 9.26]
7/μ	4/μ	5/μ	4/μ	6/μ	161	9.2171	[9.2, 9.23]

As we can see from Table 5.11, the biggest difference from constant lead time quotation policy is the increase in the profit. The profit is increased to an average of 9.33 from 4.31. The highest profit is made when L_{TH} is increased in 3^{rd}, 4^{th}, and 5^{th} reputation levels. The profit decreases when L_{TH} is increased in the 1^{st} and 2^{nd}

reputation levels. Unethical lead time quotation is given to 110 orders in average. Uniform distribution is observed in the following table.

Table 5.16. *First ten policies with basic case – uniformly distributed service & arrival time*

Lead Time Quotation Policy							
L_{TH} (1)	*L_{TH} (2)*	*L_{TH} (3)*	*L_{TH} (4)*	*L_{TH} (5)*	*Average Unethical Quotation*	*Average Profit per arrival*	*Confidence Interval*
4/μ	4/μ	4/μ	4/μ	5/μ	37	9.8136	[9.81, 9.817]
4/μ	4/μ	5/μ	5/μ	4/μ	32	9.8056	[9.801, 9.809]
4/μ	5/μ	5/μ	7/μ	4/μ	48	9.7979	[9.793, 9.802]
6/μ	4/μ	4/μ	4/μ	4/μ	15	9.7708	[9.763, 9.777]
7/μ	4/μ	4/μ	7/μ	5/μ	93	9.7463	[9.736, 9.755]
4/μ	6/μ	6/μ	5/μ	4/μ	45	9.6996	[9.69, 9.708]
4/μ	5/μ	4/μ	5/μ	7/μ	74	9.6891	[9.68, 9.698]
4/μ	5/μ	4/μ	6/μ	4/μ	28	9.6704	[9.661, 9.679]
4/μ	4/μ	6/μ	4/μ	6/μ	69	9.6512	[9.641, 9.66]
4/μ	5/μ	6/μ	4/μ	7/μ	78	9.6293	[9.619, 9.639]

When service times and arrival times are uniformly distributed random variables, the average profit per arrival is increased. L_{TH} mainly increases 4th reputation level. The profit decreases when L_{TH} is increased in the 3rd and 5th reputation levels. The results show that 1st reputation level is almost always at its lowest L_{TH} value. Unethical quotation number is decreased to 51 in average.

Tables 5.11 and 5.12 are the results when arrival rate interval is between [7, 7.72]. Now, this interval is expanded to [4, 7.72] and the results are presented in Table 5.13. The rest of the parameters stay the same as in the Table 5.10.

Table 5.17. *First ten policies – exponentially distributed service & arrival time and [LLr, ULr] = [4,7.72]*

Lead Time Quotation Policy							
L_{TH} *(1)*	L_{TH} *(2)*	L_{TH} *(3)*	L_{TH} *(4)*	L_{TH} *(5)*	*Average Unethical Quotation*	*Average Profit per arrival*	*Confidence Interval*
4/μ	4/μ	6/μ	4/μ	5/μ	55	9.4787	[9.46, 9.49]
5/μ	4/μ	5/μ	6/μ	4/μ	60	9.4525	[9.43, 9.46]
6/μ	4/μ	7/μ	6/μ	4/μ	66	9.4147	[9.4, 9.42]
5/μ	4/μ	6/μ	4/μ	6/μ	94	9.3549	[9.34, 9.36]
4/μ	6/μ	7/μ	4/μ	7/μ	117	9.3371	[9.32, 9.34]
6/μ	4/μ	6/μ	4/μ	4/μ	45	9.3141	[9.3, 9.32]
4/μ	5/μ	5/μ	6/μ	7/μ	191	9.2953	[9.28, 9.3]
4/μ	5/μ	7/μ	6/μ	4/μ	89	9.2677	[9.25, 9.28]
4/μ	7/μ	4/μ	6/μ	6/μ	132	9.2439	[9.23, 9.25]
7/μ	4/μ	4/μ	4/μ	5/μ	79	9.2110	[9.19, 9.23]

When arrival rate interval is expanded, we can see that results resembles with the ones in Table 5.11. The profit is higher when L_{TH} is increased in 3rd, 4th and 5th reputation levels. However, it is hard to find a specific pattern for the best policy. In general, L_{TH} is high in 3rd reputation level. Average unethical quotation number is 92 which is closer to the number observed in Table 5.11.

As the results show, there is an increase in the profit when we modify lead time quotation and include a policy according to the past performance of the service and satisfied customers with on-time deliveries.

5.2.2. Bernoulli Case

In this section, Bernoulli case is used to calculate the reputation levels. The parameter values are given in Table 5.14. Table 5.15 and 5.16 show the results when exponential, uniform distributions are used respectively.

Table 5.18. *Parameters for Dynamic Lead Time Model – Bernoulli Case*

Parameters	
μ	8
$[LL_r, UL_r]$	[7, 7.72]
# of rl	5
L_{max}	4/μ
L_{TH}	{4/μ, 5/μ, 6/μ, 7/μ}
d	1/μ
p	0.2
q	0.6
R	10
c	10

Table 5.19. *First ten policies with Bernoulli case – exponentially distributed service & arrival time*

Lead Time Quotation Policy							
L_{TH} *(1)*	L_{TH} *(2)*	L_{TH} *(3)*	L_{TH} *(4)*	L_{TH} *(5)*	*Average Unethical Quotation*	*Average Profit per arrival*	*Confidence Interval*
4/μ	4/μ	7/μ	6/μ	4/μ	22	9.4250	[9.41, 9.43]
4/μ	4/μ	5/μ	7/μ	4/μ	97	9.3949	[9.38, 9.4]
5/μ	4/μ	7/μ	4/μ	4/μ	117	9.3542	[9.33, 9.37]
5/μ	5/μ	4/μ	5/μ	4/μ	180	9.3226	[9.31, 9.33]
4/μ	7/μ	4/μ	4/μ	7/μ	47	9.3016	[9.29, 9.31]
5/μ	6/μ	4/μ	5/μ	7/μ	187	9.2764	[9.26, 9.29]
4/μ	6/μ	6/μ	6/μ	5/μ	118	9.2558	[9.24, 9.26]
4/μ	5/μ	6/μ	5/μ	7/μ	110	9.2349	[9.22, 9.24]
5/μ	4/μ	5/μ	7/μ	7/μ	168	9.2121	[9.2, 9.22]
5/μ	5/μ	6/μ	6/μ	5/μ	210	9.1940	[9.18, 9.2]

As it is seen from the results in Table 5.15, the average profit per arrival is nearly the same as the highest profit found in Table 5.11 which is the basic case. This means that changing reputation level calculation to Bernoulli trials do not have a significant effect on the profit generated. The best policy is observed when L_{TH} increases in 3rd and 4th

reputation levels. In the overall, we can see that L_{TH} mainly increases in 3rd and 4th reputation levels which is different from the basic case. Average unethical quotation is 125 which is higher than the observations found in previous section. Uniform distribution is tried for input variables (arrival time and service time) to see whether it leads to any different lead time quotation policy.

Table 5.20. *First ten policies with Bernoulli case – uniformly distributed service & arrival time*

Lead Time Quotation Policy							
L_{TH} (1)	*L_{TH} (2)*	*L_{TH} (3)*	*L_{TH} (4)*	*L_{TH} (5)*	*Average Unethical Quotation*	*Average Profit per arrival*	*Confidence Interval*
4/μ	4/μ	5/μ	4/μ	4/μ	18	9.8101	[9.806, 9.813]
4/μ	6/μ	6/μ	4/μ	4/μ	50	9.7992	[9.794, 9.803]
4/μ	7/μ	4/μ	5/μ	4/μ	34	9.7789	[9.774, 9.782]
4/μ	4/μ	4/μ	6/μ	5/μ	27	9.7707	[9.767, 9.773]
5/μ	5/μ	4/μ	5/μ	7/μ	111	9.7629	[9.76, 9.765]
4/μ	5/μ	4/μ	5/μ	5/μ	56	9.7560	[9.751, 9.76]
4/μ	6/μ	7/μ	4/μ	6/μ	59	9.7479	[9.745, 9.75]
4/μ	5/μ	5/μ	7/μ	4/μ	72	9.7413	[9.738, 9.744]
4/μ	6/μ	4/μ	5/μ	7/μ	47	9.7333	[9.728, 9.737]
7/μ	4/μ	4/μ	5/μ	4/μ	77	9.7248	[9.722, 9.726]

As the results show in Table 5.16 the policies do not have a specific pattern. However, higher profits are generated when L_{TH} is increased after 1st reputation level and in the reputation levels between 1st and 5th. Profit is higher than the exponential case. Average unethical lead time quotation is made for 55 orders. When arrival and service times are uniformly distributed, the L_{TH} values are almost evenly distributed between [4/μ, 7/μ]. Therefore, it is hard to observe any specific policy.

Furthermore, arrival rate interval is expanded to [4, 7.72] and the results are presented in Table 5.17. The rest of the parameters stay the same as in the Table 5.14.

Table 5.21. *First ten policies – exponentially distributed service & arrival time and [LLr, ULr] = [4,7.72]*

Lead Time Quotation Policy							
L_{TH} *(1)*	L_{TH} *(2)*	L_{TH} *(3)*	L_{TH} *(4)*	L_{TH} *(5)*	*Average Unethical Quotation*	*Average Profit per arrival*	*Confidence Interval*
4/μ	4/μ	5/μ	4/μ	7/μ	32	9.4956	[9.48, 9.5]
4/μ	4/μ	5/μ	5/μ	6/μ	37	9.4691	[9.45, 9.48]
4/μ	5/μ	5/μ	6/μ	5/μ	64	9.4430	[9.43, 9.45]
4/μ	5/μ	4/μ	4/μ	5/μ	24	9.4152	[9.39, 9.43]
4/μ	4/μ	4/μ	4/μ	4/μ	0	9.3874	[9.37, 9.39]
4/μ	7/μ	5/μ	5/μ	4/μ	49	9.3661	[9.35, 9.37]
4/μ	4/μ	7/μ	6/μ	7/μ	34	9.3426	[9.32, 9.35]
5/μ	6/μ	4/μ	6/μ	6/μ	97	9.3164	[9.3, 9.32]
5/μ	7/μ	5/μ	5/μ	5/μ	108	9.2941	[9.28, 9.3]
6/μ	7/μ	4/μ	6/μ	4/μ	122	9.2690	[9.25, 9.28]

When arrival rate interval is expanded, L_{TH} is decreased for the low reputation levels. Unethical quotation is 56 in average which is lower than the case represented in Table 5.15.

5.2.3. Average Case

In this section, reputation level is calculated based on the past reputation levels. After each service completion the average of previous reputation levels is calculated to determine the new arrival rate. The parameter values are given in Table 5.18. Table 5.19 and 5.20 show the results when exponential, normal distributions are used respectively.

Table 5.22. *Parameters for Dynamic Lead Time Model – Average Case*

Parameters	
μ	8
$[LL_r, UL_r]$	[7, 7.72]
# of rl	5
L_{max}	4/μ
L_{TH}	{4/μ, 5/μ, 6/μ, 7/μ}
d	1/μ
σ_a	0.15
σ_s	0.1
R	10
c	10

Table 5.23. *First ten policies with Average case – exponentially distributed service & arrival time*

Lead Time Quotation Policy							
L_{TH} *(1)*	L_{TH} *(2)*	L_{TH} *(3)*	L_{TH} *(4)*	L_{TH} *(5)*	*Average Unethical Quotation*	*Average Profit per arrival*	*Confidence Interval*
7/μ	4/μ	5/μ	4/μ	7/μ	118	9.4172	[9.4, 9.43]
6/μ	4/μ	5/μ	5/μ	7/μ	11	9.3867	[9.36, 9.4]
5/μ	4/μ	5/μ	7/μ	6/μ	7	9.3159	[9.26, 9.36]
5/μ	5/μ	6/μ	5/μ	6/μ	12	9.2546	[9.24, 9.26]
7/μ	5/μ	7/μ	5/μ	5/μ	29	9.2324	[9.22, 9.24]
7/μ	6/μ	5/μ	4/μ	4/μ	53	9.2138	[9.2, 9.22]
4/μ	6/μ	4/μ	4/μ	4/μ	168	9.1953	[9.18, 9.2]
5/μ	4/μ	6/μ	4/μ	5/μ	349	9.1732	[9.16, 9.18]
6/μ	5/μ	6/μ	7/μ	5/μ	315	9.1470	[9.13, 9.16]
6/μ	4/μ	6/μ	4/μ	4/μ	421	9.1240	[9.11, 9.13]

As it is seen from the results above, L_{TH} observations in 1st and 5th reputation levels are completely different from other cases. The policies ranked higher in the table is close to a convex shaped pattern of L_{TH} values. Profit is almost the same with the cases observed in the previous sections with exponential distributions. Unethical quotation increases as the profit decreases. The average unethical quotation is 148.

The results of normally distributed input variables are presented in the Table 5.20.

Table 5.24. *First ten policies with average case – normally distributed service & arrival time*

Lead Time Quotation Policy							
L_{TH} (1)	*L_{TH} (2)*	*L_{TH} (3)*	*L_{TH} (4)*	*L_{TH} (5)*	*Average Unethical Quotation*	*Average Profit per arrival*	*Confidence Interval*
7/μ	4/μ	4/μ	5/μ	6/μ	98	9.5691	[9.55, 9.58]
6/μ	7/μ	4/μ	4/μ	6/μ	12	9.4767	[9.44, 9.5]
7/μ	6/μ	4/μ	4/μ	6/μ	58	9.4159	[9.39, 9.43]
6/μ	4/μ	4/μ	4/μ	7/μ	76	9.3783	[9.36, 9.39]
6/μ	7/μ	5/μ	4/μ	7/μ	86	9.3503	[9.33, 9.36]
7/μ	4/μ	4/μ	7/μ	6/μ	139	9.3265	[9.31, 9.33]
5/μ	7/μ	5/μ	5/μ	6/μ	151	9.3038	[9.29, 9.31]
6/μ	6/μ	4/μ	7/μ	6/μ	6	9.2795	[9.26, 9.29]
5/μ	7/μ	5/μ	4/μ	6/μ	0	9.2482	[9.23, 9.26]
5/μ	4/μ	4/μ	4/μ	6/μ	0	9.2141	[9.19, 9.23]

When normal distribution is used for input variables, the same pattern is observed which is also seen in Table 5.19. The 1st and 5th reputation level have high L_{TH} values whereas it decreases in-between. Average profit per arrival is increased by 0.01%. In average 62 unethical quotations have been made.

In the following Table 5.21 and Table 5.22 average case is observed under narrowed and expanded arrival rate interval.

Table 5.25. *First ten policies – exponentially distributed service & arrival time and [LLr, ULr] = [4,5]*

Lead Time Quotation Policy							
L_{TH} (1)	L_{TH} (2)	L_{TH} (3)	L_{TH} (4)	L_{TH} (5)	*Average Unethical Quotation*	*Average Profit per arrival*	*Confidence Interval*
7/μ	5/μ	4/μ	4/μ	4/μ	201	9.4791	[9.46, 9.49]
6/μ	5/μ	4/μ	4/μ	4/μ	1	9.3895	[9.37, 9.4]
7/μ	4/μ	5/μ	5/μ	4/μ	13	9.3551	[9.33, 9.37]
7/μ	4/μ	4/μ	5/μ	4/μ	22	9.3249	[9.31, 9.33]
7/μ	5/μ	4/μ	5/μ	4/μ	54	9.2983	[9.27, 9.31]
7/μ	4/μ	4/μ	6/μ	4/μ	38	9.2616	[9.24, 9.27]
7/μ	6/μ	5/μ	5/μ	4/μ	65	9.2321	[9.21, 9.24]
5/μ	6/μ	6/μ	5/μ	5/μ	70	9.1943	[9.17, 9.21]
6/μ	6/μ	5/μ	5/μ	7/μ	137	9.1626	[9.14, 9.17]
6/μ	7/μ	5/μ	6/μ	6/μ	118	9.1285	[9.11, 9.14]

As Table 5.21 shows, when arrival rate interval is narrowed down to [4,5], the same pattern as the results in Table 5.19 and 5.20 has not been observed. The best policy is when L_{TH} increases in the 1st reputation level. The first 10 policy shows us that increasing 1st reputation level order acceptance to allow unethical quotation leads to higher profits if a seller has average rates of arrival. 71 orders are quoted with unethical practice in average. However, unethical quotation increases as L_{TH} increases in the high reputation levels.

Table 5.26. *First ten policies – exponentially distributed service & arrival time and [LLr, ULr] = [4,7.72]*

Lead Time Quotation Policy							
L_{TH} *(1)*	L_{TH} *(2)*	L_{TH} *(3)*	L_{TH} *(4)*	L_{TH} *(5)*	*Average Unethical Quotation*	*Average Profit per arrival*	*Confidence Interval*
7/μ	5/μ	4/μ	4/μ	6/μ	193	9.3201	[9.3, 9.33]
7/μ	5/μ	5/μ	4/μ	6/μ	26	9.2871	[9.26, 9.3]
6/μ	4/μ	4/μ	4/μ	6/μ	57	9.2481	[9.23, 9.26]
7/μ	5/μ	4/μ	5/μ	7/μ	62	9.2078	[9.18, 9.23]
6/μ	5/μ	4/μ	4/μ	7/μ	87	9.1690	[9.15, 9.18]
7/μ	7/μ	4/μ	4/μ	6/μ	97	9.1361	[9.11, 9.15]
6/μ	5/μ	6/μ	5/μ	7/μ	110	9.1005	[9.08, 9.11]
5/μ	4/μ	5/μ	5/μ	4/μ	158	9.0719	[9.06, 9.08]
7/μ	4/μ	5/μ	5/μ	6/μ	192	9.0442	[9.02, 9.05]
5/μ	5/μ	4/μ	5/μ	7/μ	47	9.0077	[8.98, 9.02]

When arrival rate interval is expanded to [4, 7.72], the results show that L_{TH} mainly increases in 1st and 5th reputation levels. This is the same pattern observed in Tables 5.19 and 5.20. However, it is more accurate in this case that the 1st and 5th reputation levels have high L_{TH} when it is compared to the reputation levels in-between. Almost in each policy presented above, L_{TH} values are not higher than 5/μ for 2nd, 3rd and 4th reputation levels. Unethical lead time quotation is 102 in average. However, unethical quotation does not bring additional profit when L_{TH} is increased in the middle reputation levels.

If the results shown in Tables 5.19, 5.21 and 5.22 are compared, we see that the case when arrival rate interval is narrowed down, L_{TH} behavior is different than the expanded and high arrival rate intervals scenarios. Table 5.22 might be interpreted as the big picture of average case, while Tables 5.19 and 5.21 are the parts of this picture. Therefore, the pattern is more accurate and visible as a convex shape in Table 5.22.

5.3. Overview of Numerical Analysis

In this section, the results we represented previously are summarized to have a better understanding of the performance of different cases. When observations in Section 5.1 and 5.2 are compared, we conclude that dynamic lead time quotation policies might bring additional profit when arrival rates are high, and the arrival rate intervals are wide.

To compare the results of Section 5.2, Table 5.23 shows the maximum average profit and unethical quotation which are the results of the best policy for each case.

Table 5.27. *Overview of previous results*

		$[LL_r, UL_r] = [7,7.72]$		$[LL_r, UL_r] = [4,7.72]$	
		Unethical quotation	g_k	Unethical quotation	g_k
Basic	Exponential	84	9.4290	55	9.4787
	Uniform	37	9.8136	-	-
Bernoulli	Exponential	22	9.4250	32	9.4956
	Uniform	18	9.8101	-	-
Average	Exponential	118	9.4172	193	9.3201
	Normal	98	9.5691	-	-

As the Table 5.23 shows, the average profit per arrival has not changed for basic, Bernoulli and average cases when exponential distribution is used for the input variables, i.e. service and interarrival times. Although there isn't any specific pattern of L_{TH} found for basic and Bernoulli cases, we can say that these both cases do not support increasing L_{TH} in the lower reputation levels. The table also shows that average case is the one where unethical quotation is mostly practiced and the Bernoulli case is the one unethical quotation is practiced at least. When the arrival rate interval is expanded, again in average case unethical quotation is more than the other cases. The average profit per arrival is lower in the average case when the arrival rate interval is expanded.

The results of average case are plotted as in Figure 5.1 to see the pattern of L_{TH} more clearly. The results represented in Table 5.22 is the first ten lead time quotation policies when $[LL_r, UL_r]$ = [4,7.72] and the confidence intervals of average profit do not overlap each other. In the following plot, all the policies including the ones in-between these first ten policies with overlapping confidence intervals are considered as well. Therefore, the plot illustrates the mode of the value that L_{TH} gets in each reputation level. The mode is higher as the circle gets bigger.

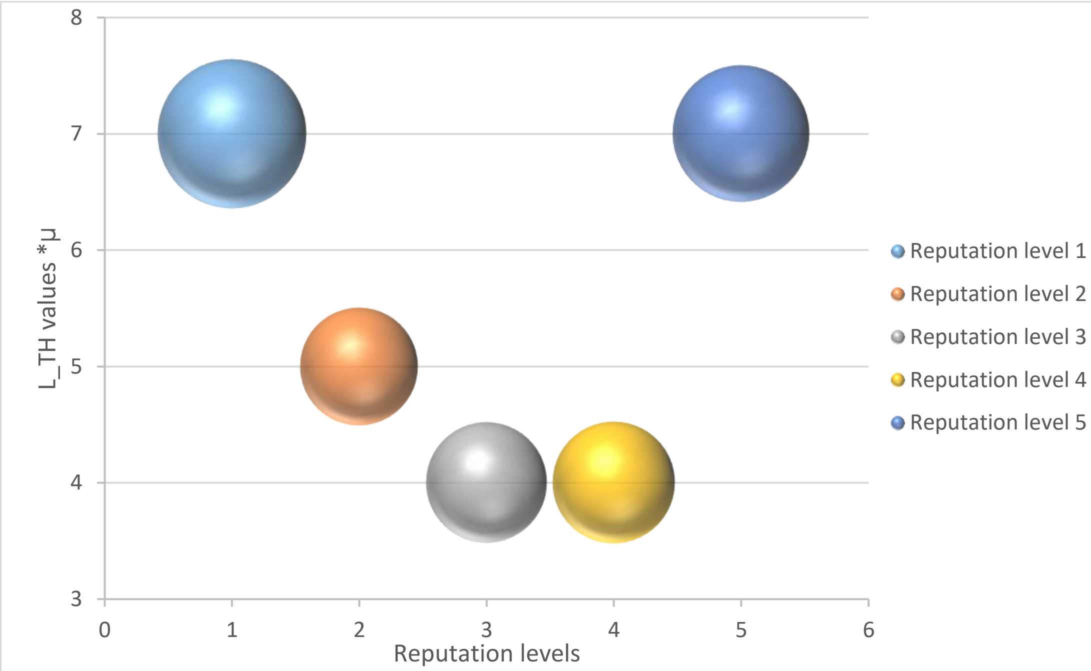

Figure 5.2. Mode of L_{TH} values according to the reputation levels

Figure 5.2 shows the convex shape of L_{TH} behavior when average case is used as a reputation level calculation method. According to the plot, L_{TH} is at its highest value in 1st and 5th reputation levels while it decreases in 2nd,3rd and 4th reputation levels.

CHAPTER 6

MANAGERIAL INSIGHTS

In the previous chapters, an M/M/1 queueing environment is modeled under specific conditions. With the help of the constructed simulation model, we have discussed lead time quotation strategies under reputation level constraints and unethical practices. However, it is important to relate these results with real life practices. In this chapter, the business perspective of this thesis will be discussed.

The focus of this study is e-commerce environment. As mentioned in the Chapter 3, a study about e-commerce websites and the results of a survey show that reviews and ratings influence the decision of customer. In other words, arrival rate of customers has a positive correlation with reviews and ratings (Flanagin et al., 2014).

According to another research, the total number of reviews and the quality of them affect the decision of the purchaser (Hu, Liu, & Zhang, 2008). The research is based on the data gathered from Amazon.com's Web Services and the authors have examined the reaction of the purchasers to the online reviews within different concepts such as the effect of online reviews on sales over time, reviewer quality, reviewer exposure and the product coverage. According to these results, the quality of the reviews is as important as the quantity. Another study conducted by D. Park, J. Lee, I. Han about how the purchasing intention changes with the reviews' quantity and quality shows us changes in the sales volume is correlated with online reviews (Hu et al., 2008). Therefore, to comment on our results for an e-commerce website, review and rating systems in well-known websites are investigated.

Some examples are presented below from Amazon.com, n11.com, gittigidiyor.com (which is acquired by E-bay) and hepsiburada.com to understand different rating systems.

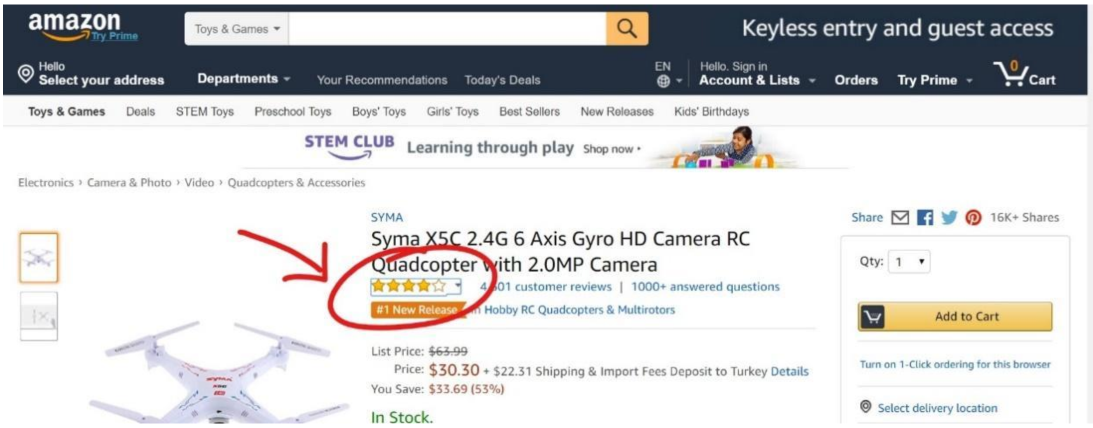

Figure 6.1. Amazon.com

Amazon.com uses 5-star rating system for each product. The star number is calculated with the average ratings that the customers have given to the product considering the service and if they are satisfied with the product or not. Customers are able to see the total rating, or they can reach each review in detail which may have an effect on their purchasing intention.

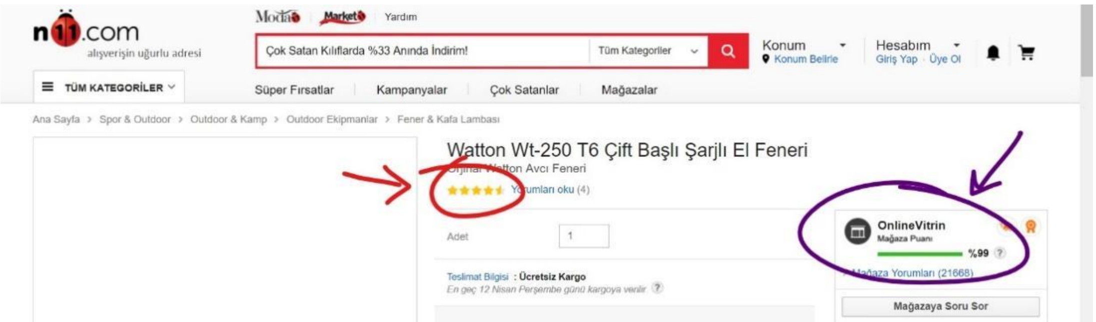

Figure 6.2. n11.com

The second example is from n11.com which is one of the well-known e-commerce websites founded in Turkey. As seen above, the product is rated out of 5 stars and the seller has another score which is out of 100. These scores are based on the overall performance of the seller. The seller’s overall performance score is calculated based on the average shipping time, on-time deliveries, total amount of sales. The purchaser can see product reviews and seller’s reviews separately.

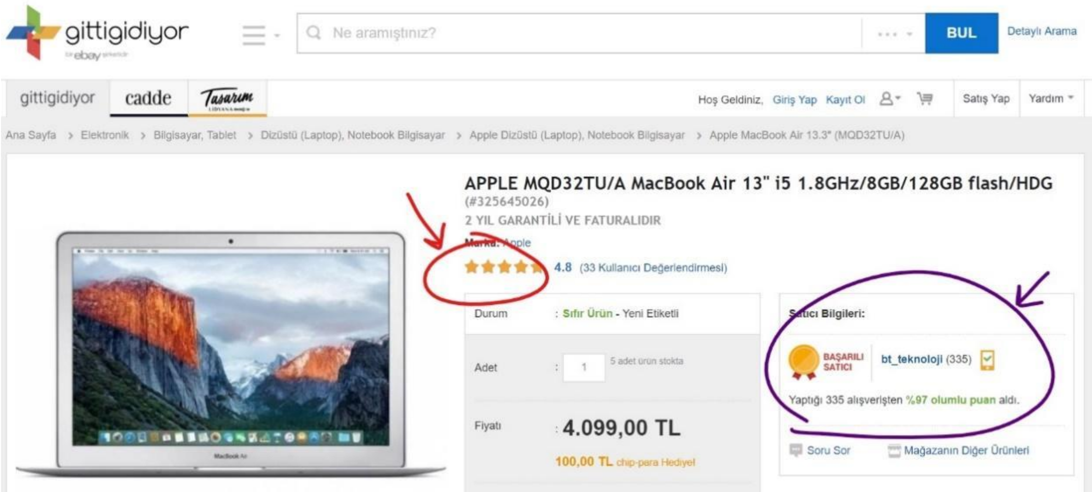

Figure 6.3. gittigidiyor.com

Another example is from gittigidiyor.com, which has been acquired by E-bay recently. The rating systems are same as n11.com. The product is rated out of 5 stars while the seller has a score out of 100.

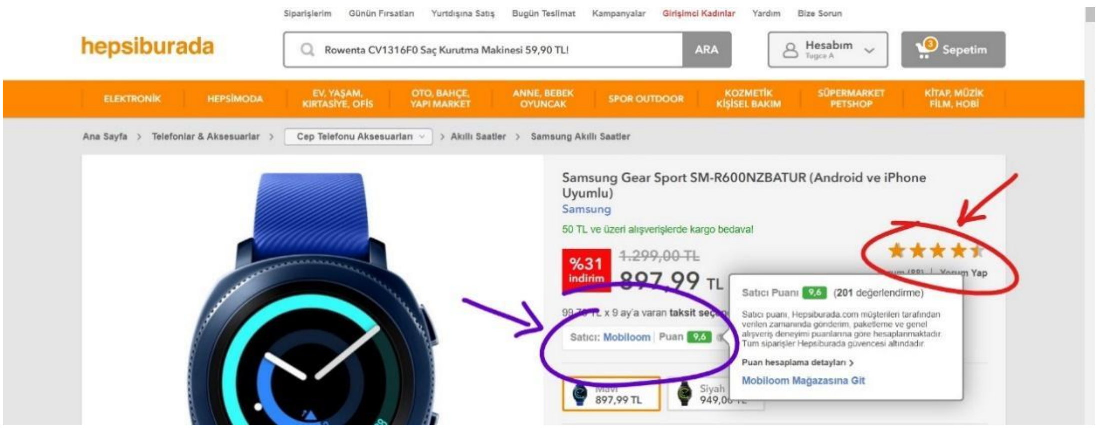

Figure 6.4. hepsiburada.com

The last example is from hepsiburada.com. The product is rated out of 5 stars while the seller has a score out of 10. The performance score of the seller is calculated by considering on-time deliveries, the average rating from other products the same seller has, the reviews of customers about the service.

These platforms mostly have their special algorithm to calculate the overall seller score. This algorithm uses the average of the past ratings of a product regarding a seller which is interpreted as average case in the scenarios introduced in Chapter 5. Therefore, we also consider average case while interpreting these results as an insight for an e-commerce seller.

In the following part, we will discuss if these rating scores could be treated as the *reputation levels* in our model. If we assume the score indicators represent the *reputation levels* that we have in our model, then there could be policies to introduce about the unethical practice and lead time quotation for different settings.

The rest of this chapter is divided into two subtitles. Under first one, we try out 10 reputation levels in the simulation model and represent the results. In the second section, policies are discussed based on *unethical quotation* and *threshold lead time* (L_{TH}) that we have introduced in our model.

6.1. Scenario with 10 reputation levels

As it is discussed in the beginning of Chapter 6, most of the well-known e-commerce platforms use 5-star rating methods while some of them rate the seller out of 10 as well. Therefore, we try the average case with 10 reputation levels to see the L_{TH} behavior of lead time quotation policies.

The parameters are listed in Table 6.1. Exponential distribution is used for the service and interarrival times.

Table 6.1. *Parameters for Average Case with 10 reputation levels*

Parameters	
μ	8
$[LL_r, UL_r]$	[4, 7.72]
L_{max}	$4/\mu$
L_{TH}	$\{4/\mu, 5/\mu, 6/\mu, 7/\mu\}$
d	$1/\mu$
R	10
c	10

Table 6.2. *First ten policies – exponentially distributed service & arrival time and [LLr, ULr] = [4,7.72]*

Lead Time Quotation Policy												
L_{TH} *(1)*	L_{TH} *(2)*	L_{TH} *(3)*	L_{TH} *(4)*	L_{TH} *(5)*	L_{TH} *(6)*	L_{TH} *(7)*	L_{TH} *(8)*	L_{TH} *(9)*	L_{TH} *(10)*	*Average unethical quotation*	g_k	*95% Confidence Interval*
6/μ	5/μ	6/μ	5/μ	4/μ	4/μ	5/μ	4/μ	7/μ	6/μ	227	9.41	[9.39, 9.43]
7/μ	6/μ	5/μ	4/μ	5/μ	4/μ	5/μ	6/μ	7/μ	7/μ	239	9.36	[9.34, 9.37]
6/μ	5/μ	5/μ	4/μ	5/μ	5/μ	4/μ	6/μ	6/μ	7/μ	352	9.31	[9.29, 9.32]
6/μ	6/μ	4/μ	5/μ	5/μ	5/μ	4/μ	6/μ	6/μ	7/μ	347	9.26	[9.23, 9.29]
6/μ	7/μ	5/μ	4/μ	6/μ	7/μ	6/μ	4/μ	5/μ	6/μ	75	9.19	[9.16, 9.22]
7/μ	7/μ	7/μ	7/μ	7/μ	4/μ	4/μ	4/μ	4/μ	4/μ	32	9.14	[9.12, 9.16]
7/μ	5/μ	4/μ	5/μ	5/μ	5/μ	4/μ	6/μ	4/μ	7/μ	323	9.09	[9.06, 9.12]
4/μ	4/μ	4/μ	4/μ	4/μ	7/μ	7/μ	7/μ	7/μ	7/μ	343	9.03	[9, 9.06]
4/μ	5/μ	4/μ	7/μ	7/μ	6/μ	6/μ	5/μ	4/μ	4/μ	382	8.93	[8.9, 8.96]
4/μ	5/μ	5/μ	6/μ	7/μ	7/μ	7/μ	6/μ	4/μ	5/μ	397	8.87	[8.84, 8.9]

As the results in Table 6.2 show, when L_{TH} is increased in the low and high reputation levels, the average profit per arrival increases as well. In the 6th policy we see that lower reputation levels are at its highest value and higher levels are at its lowest value and in the 8th policy the higher reputation levels are at the highest value while the lower reputation levels are at the lowest value. If their performances are compared, we can conclude that 8th policy is not as profitable as 6th one. So, increasing the L_{TH} and accepting more orders in lower reputation levels would bring more profit. The average unethical quotation is 272 which is higher than the cases with 5 reputation levels.

6.2. Unethical Quotation and Threshold Lead time

In the online commercial channels, reviews and ratings play an important role for purchasing decisions. There are various researches reported in the literature about this role, some of which are mentioned in the chapters above and these studies show that buying decision of the customer is affected positively or negatively with the past performance of the firm. As e-commerce is getting more popular every day, it becomes a necessity for the rating and review platforms to be more user-friendly and transparent. As opposed to the past decade, today one can find more details about the firm's past performance. Moreover, there is an increasing trend for the firms to take part in the e-commerce business as the technology and internet takes over our daily routine. In such a competitive environment, firms, who want to increase their profit, need to consider useful control mechanisms such as *lead time quotes* for deriving useful policies.

In Chapter 5, change in the unethical quotation is analyzed based on L_{TH} under different conditions. If reputation levels can be represented by the rating scores or the stars in the online commercial sites, then *lead time quotation* policy of a seller can be shaped accordingly.

If a seller controls their order acceptance, i.e. L_{TH} value, deliberately, they might increase their profit as it is shown in Table 5.19, 5.20, 5.21, 5.22. According to the settings we have established, *threshold lead time* is used by the firm to control the acceptance rate at different reputation levels. Considering its past performance, a firm determines L_{TH} for every reputation level. In the results shown in Table 5.19, more profit is generated when L_{TH} value is increased in lower and higher reputation levels and decreased in-between. In other words, if a firm has poor performance, which means negative reviews in online channels, then they might increase their profit by accepting more orders and quoting short lead times on purpose. By this way, they will have more chance to serve and their probability of on-time delivery increases as they are already having low arrival rates. Also, if a firm already has a positive review and good performance, it may increase L_{TH} and accept more customers in the system since it does not need to focus on on-time delivery performance. Calculating the overall score for a seller from the average of past ratings makes it hard to drop a score, so tardiness cost become relatively less important for a seller who already has a lot of customers coming in.

When the arrival rate intervals can be determined, if a seller is operating in low arrival rates as simulated in Table 5.21, accepting more orders in low reputation levels might help to increase the customer portfolio and increase the chances of future sales. However, if the arrival rate interval is high, then it is also advantageous to accept more orders in high reputation levels as well.

CHAPTER 7

CONCLUSION

The relevant literature suggests many models and algorithms in the scope of lead time quotation. There are various researches conducted to find an optimal policy for determining lead times. These policies include minimizing the cost of tardy jobs, delay, queue length or maximizing the revenue and earliness.

In this study, we try to investigate the reputation level focusing on its effects on the lead time quotation of a seller. The idea is finding the structure of the lead time quotation policy in an e-commerce environment, where the past performance becomes more important with the advances in information technology. We have proposed a model and its variations considering additional factors.

Firstly, the problem is modeled as a Semi Markov Decision Process (SMDP), where each arrival is a decision epoch for the state transition. Value function and SMDP recursion is detailed in Chapter 4. However, as there is an infinite state space for this process, we used simulation to try different scenarios and find an optimal lead time quotation policy.

Our simulation model is a single server queueing system where the server/firm determines the lead time for different reputation levels. The reputation level specifies customer arrival rates. In the model, reputation level is considered as the past performance score/ratings found in e-commerce websites. The firm decides the *quoted lead time* considering its rating, i.e. past performance. Being tardy, i.e. sending orders later than the promised time, has a penalty that decreases the reputation level and the revenue. On the contrary, being on-time, i.e. sending orders before or on the due date, has a reward that increases the reputation level and the revenue of the server. With the fast development in technology, there are many choices for a firm who plans to utilize an online channel. These online channels have various aspects (like rating/scoring method) that differs from one to another. We have also tried to understand the managerial impacts of these different rating/scoring methods or past performance indicators. We refer the rating scale of e-commerce websites as *reputation level numbers*.

In the simulation model we have proposed, the results show that a firm tends to quote short lead times without considering being on-time or tardy if they are operating in high *reputation levels*. Quoting a short lead time when we know that the job will not be sent on-time is considered as *unethical quotation*. Basically, we investigate the effects of *unethical quotation, reputation levels, quoted lead time, customer's willingness to wait, threshold lead time* (L_{TH}) *in different reputation levels*.

First question is the difference between constant and dynamic lead time quotation with or without unethical quotation. The other questions are about the effects of order acceptance decision and policy of lead time quotation.

Firstly, we analyze the simplest system where a seller quotes a constant lead times to each customer for all reputation levels and no unethical quotation is allowed. The results of this scenario are used as a benchmark. We tried different values for the constant lead time and used different distributions for the input variables. The results show that if the arrival rate is high, constant lead time quotation is not advantageous. However, when there is low arrival rate, high profits are observed. This is expected since the tardiness cost is lower at lower arrival rates of customers. However, this case is not realistic as in this policy it is assumed that customers accept all lead time quotations regardless of its length and ignores the competition in the market.

Secondly, since using constant lead time is not realistic, we consider the lead times that are quoted dynamically. *Expected completion time* of a customer is calculated by adding expected tardiness to the expected service time. The results show that dynamic lead time quotation increases the profit even when the arrival rates are high.

The *unethical quotation* concept is implemented with L_{TH} and the maximum value of lead time that a customer accepts (L_{max}). A lead time is calculated and either this lead time or L_{max} is quoted to the customer. If the customer is not patient enough to wait, which means L_{max} is less than the *expected completion time* (T_E), L_{max} is used instead of a calculated lead time which leads to the *unethical practice*.

Three different cases are introduced for reputation level calculation, basic case where the reputation levels are increased/decreased after each service completion. In the Bernoulli case, the reputation levels are increased/decreased according to a Bernoulli trial, with a success probability of p. In the average case, the reputation level is calculated as an average of previous reputation levels. This case is the mostly used one in real life when well-known e-commerce platforms are considered.

Throughout the scenarios implemented with these three cases, unethical quotation numbers vary in similar intervals. Unethical quotation number is higher when exponential distribution is used for input random variables. It decreases when arrival rate interval is narrowed down.

For the basic and Bernoulli cases we couldn't find any specific pattern for the best L_{TH} choice, i.e. lead time quotation policy. However, L_{TH} is mostly increased in the higher reputation levels. For average case, a convex shaped pattern is observed. L_{TH} is increased in the 1st and 5th reputation levels and decreased in-between.

In chapter 6, we discuss the managerial impacts of our model. The results show that, if a seller wants to increase the profit, s/he needs to increase its rating score. The past performance affects the customer purchasing decision directly. Therefore, a seller needs to maintain the high reputation levels as long as possible. E-loyalty becomes more important for low reputation levels and when there are few reputation levels in the system.

This study can be extended by related future work. Our assumption in this thesis is a First-Come-First-Served (FIFO) M/M/1 queue system. One can experiment with an improved model where there are priorities and categories of customers. The environment setting for an optimal policy can be determined. Also, we use only one cost parameter which is the tardiness of an order. In future models, one can consider additional cost parameters. Obviously, real data may be used in the simulation model which might lead to more accurate solutions.

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