THE VALUE OF INFORMATION IN A MANUFACTURING FACILITY TAKING PRODUCTION AND LEAD TIME QUOTATION DECISIONS

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ABSTRACT

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Advancements in information technology enabled to track real time data in a more accurate and precise way in many manufacturing facilities. However, before obtaining the more accurate and precise data, the investment in information technology should be validated. Value of information may be adopted as a criterion in this investment. In this study, we analyze the value of information in a manufacturing facility where production and lead time quotation decisions are taken. In order to assess the value of information, two settings are analyzed. Under the first setting, the manufacturer takes decisions under perfect information. To find the optimal decisions under perfect information, a stochastic model is introduced. Under the second setting, the manufacturer takes decisions under imperfect information. To obtain a solution for this problem, Partially Observable Markov Decision Process is employed. Under the second setting, we study two approaches. In the first approach, we introduce a nonlinear programming model to find the optimal decisions. In the second approach, a heuristic approach, constructed on optimal actions taken under perfect information is presented. We examine the value of information under different parameters by considering the policies under nonlinear programming model and heuristic approach. The profit gap between the two policies is investigated. The effect of Make-to-Order (MTO) and Make-to-Stock (MTS) schemes on the value of information is analyzed. Lastly, different lead time quotation schemes; accept-all, accept-reject and precise lead time; are compared to find under which quotation scheme value of information is highest.

Keywords: Value of Information, Markov Decision Process, Partially Observable Markov Decision Process, Production Control, Lead Time Quotation

ÖZ

ÜRETİM VE TEDARİK SÜRESİ KARARLARINI VEREN BİR ÜRETİM TESİSİNDE BİLGİNİN DEĞERİ

Kaman, Cumhur
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Bilgi teknolojisindeki gelişmeler, birçok üretim tesisinde gerçek zamanlı verilerin takip edilmesine olanak sağlamaktadır. Ancak, doğru ve kesin verilerin elde edilmesinden önce, bilgi teknolojisindeki yatırımın doğrulanması gerekmektedir. Bilginin değeri, bu yatırım için bir ölçüt olarak kullanılabilir. Bu çalışmada, üretim ve tedarik zamanı kararlarını alan bir üretim tesisinde bilginin değeri analiz edilmektedir. Bilginin değerini tespit edebilmek amacıyla, iki durum analiz edilmektedir. Birinci durum altında, üretici kararlarını şeffaf bilgi altında almaktadır. Şeffaf bilgi altında en uygun kararları elde edebilmek için, rassal bir model kurulmuştur. İkinci durum altında, üretici kararlarını şeffaf olmayan bilgi altında almaktadır. Şeffaf olmayan bilgi altında alınan en uygun kararları belirlemek amacıyla Kısmi Gözlemlenebilen Markov Karar Süreci kullanılmaktadır. İkinci durum altında, iki yaklaşım üzerinde çalışılmaktadır. Birinci yaklaşımda, en uygun kararları elde edebilmek için doğrusal olmayan bir model kurulmaktadır. İkinci yaklaşımda, şeffaf bilgi altında alınan en uygun kararlardan faydalanan sezgisel bir yaklaşım geliştirilmiştir. Doğrusal olmayan model ve sezgisel yaklaşım altında alınan politikalar kullanılarak, farklı parametreler altında, bilginin değeri incelenmektedir. İki farklı politika altındaki kâr farklarının nedenleri araştırılmıştır. Sipariş üzerine üretim politikası ile stok politikalarının bilginin değeri üzerindeki etkisi analiz edilmektedir. Son olarak, farklı tedarik süresi bildirme politikalarının; bütün müşterileri kabul et, müşterileri kabul et ya da reddet ve kesin tedarik süresi; bir karşılaştırması yapılmış ve bilginin değerinin en fazla olduğu politikalar belirlenmiştir.

Anahtar kelimeler: Bilginin Değeri, Markov Karar Süreci, Kısmi Gözlemlenebilen Markov Karar Süreci, Üretim Kontrolü, Tedarik Süresi Bildirme

To my family and Altan Özen…

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λ	Customer arrival rate
μ	Service rate
d	Lead time / due date
R	Revenue per customer
ℓ	Penalty / lateness cost per item, per unit time charged for the amount of time later than the quoted due date
h	Holding cost per unit per unit time for the items in inventory
$f(d)$	Acceptance probability of a customer quoted a due date of d
$L_i(d)$	Expected amount of delay for a customer arriving in state i and quoted the lead time d
g	Optimal average profit (per transition)
$O(i'\|i)$	Probability of observing state i' when the actual state is i
$\alpha_{i'a}$	Probability of taking action a when the observed state is i'
$p(j\|i, a)$	Probability that next state will be j given that the state is i and action a is taken
$p(j, j'\|i, i', a)$	Probability that next state will be (j, j') given that the state is (i, i') and action a is taken
r_{ia}	Expected one-step reward obtained in state i under action a
$r_{ii'a}$	Expected one-step reward obtained in actual state i under action a when the observed state is i'
$r_{ii'}$	Expected one-step reward obtained in actual state i when the observed state is i'

π_{ia} Long run fraction of time at which the system is in state i and action a is taken

$\pi_{ii'a}$ Long run fraction of time when the actual state is i, observed state is i' and action a is taken

$\pi_{ii'}$ Long-run fraction of time at which the system is in actual state i and observed state i'

CHAPTER 1

INTRODUCTION

Companies are racing to take place in the global market which is dynamic in nature and electronically connected (Gunasekaran and Ngai, 2004). In this market, information is absolutely crucial in decision making. Especially, under uncertainty, decision making is inherently related to information and its availability (Eckwert and Zilcha, 2001). The advancements in information technology has enabled to gather the necessary information before the company makes a decision. In this context, many firms benefit from information technology in supply chain operations. As given in Simchi-Levi and Zhao (2004) "Information technology has changed the way companies collaborate with suppliers and customers". These collaborations have achieved great success in inventory reduction and service level improvement by the help of real time data. However, the real time data may contain errors or it cannot be accessed under all circumstances due to observability constraints, leading to an increase in the uncertainty. On the other hand, the more accurate information, the better the company is able to reduce the uncertainty coming with the decision (Oestreich and Buytendijk, 2010). Therefore, the "value of information" gains importance.

As mentioned, because of the observability constraints, the real-time data in production may be corrupted or even not be tracked. The observability constraints may result from many factors. For instance, errors, leading to the inaccuracy of inventory records, may arise due to "incorrect product identification, transaction errors, inaccessibility of items due to improper usage of the depot, misplacements and shrinkage" (Uçkun, Karaesmen, and Savaş, 2008). Inaccuracy of inventory records may lead to ineffective replenishment decisions. Another example would be related with the status of production. Consider a manufacturing facility where status of production is closely tracked by the help of Radio Frequency Identification (RFID) tags. An example for this is "Ford's wireless kanban system based on RFID, which improved tracking of parts through the assembly process" (Tajima, 2007). However, in general, there are risks associated with employing RFID tags. For instance, the radio waves sent from tags has the potential of being "absorbed by moisture or can be hidden or distorted by metal and noise from electric motors and fluorescent lights"(Hingley, Taylor, and Ellis, 2007). Also, there may occur tag collision, where the signals sent from tags interfere with one another, or system failures due to the mistakes made by the employees causing the system to be inaccessible for a period of time (Higgins and Cairney, 2006). Therefore, the exact status of production may not be observed or tracked at all times.

In this study, we analyze the value of information in a manufacturing facility where production and lead time quotation decisions are made. In particular, we consider a manufacturer who cannot observe the current state of production, but rather gets inaccurate information about the current state. There are many examples of this situation in production facilities. For instance, consider the lag between the time at which a production event occurs and the time at which this information is entered into a computer system. The production visibility will be reduced and the manufacturer controlling the production status from this computer system cannot obtain the accurate information for a period of time. Another example for not obtaining accurate information may result from imperfect automatic data capture systems, such as RFID, used to track the status of production. Consider a production facility where serial N operations are performed to obtain the final product. Assume that the status of the production is tracked by an RFID system, which updates the current status, when the product passes from one workstation to another workstation. When the signals sent from a tag attached to a semi-finished product is read by multiple readers located at different workstations simultaneously, the current status is not going to be directly observable but partially observable. In these kind of situations, since the manufacturer cannot access to accurate information (the number of items waiting in the inventory or the number of outstanding orders), inefficient decisions, causing extra holding/penalty costs to incur, will be made.

To assess the value of information, performance measures under perfect and partial information will be compared. The manufacturer will be examined under two settings. In the first setting, the manufacturer can observe the actual state of the production, i.e. the manufacturer can access to perfect information about the exact status of production. This might be the case where production status is tracked via RFID. We present a stochastic model to find the optimal decisions under perfect information. Under the second setting, the manufacturer cannot observe the actual state of production. Instead, the manufacturer "can only observe imperfect signals of the system state" (Zhang, 2010), i.e. the manufacturer can get imperfect information about the actual state of the production. This might be the case when the manufacturer is operating under a system with no RFID. To obtain a solution for this problem, Partially Observable Markov Decision Process (POMDP) will be employed. Under the second setting, two approaches are developed. The first approach to the problem is a nonlinear model. The second approach is a heuristic policy constructed on actions taken under perfect information.

The remainder of this study is organized as follows. The related literature is reviewed in the following chapter. In Chapter 3, we represent the models and the underlying assumptions. Numerical analyses are given in Chapter 4. The comparison of the manufacturer under the first and second settings and the observations are presented in this chapter. In Chapter 5, we conclude our study by representing suggestions on future work.

CHAPTER 2

LITERATURE SURVEY

In this study, we consider the value of information in a manufacturing facility where the exact status of production is not observable. The manufacturer takes production and lead time quotation decisions. Hence, the focus of the literature review is on lead time quotation decisions and value of information.

2.1 Sharing Lead time Information

Due date management policies have received much attention in the literature. In this section, we will only consider the ones where the manufacturer shares the lead time information with the lead time sensitive customers. Note that, the studies given in this section assume that the decisions are taken under perfect information.

Duenyas and Hoop (1995) consider the profit maximization problem of a manufacturer quoting lead times and sequencing the lead time sensitive customers in a Make-to-Order (MTO) environment. In this paper, three models are considered. In the first model, an infinite capacity manufacturer is examined. In the second model, a finite capacity plant is considered. The authors investigate the model in two parts; the first one, accept-reject policies and the second one "variable lead times". The first part reveals the structure of an optimal policy for the manufacturer depending on the number of customers waiting. The second part proves that the longer lead times should be quoted when the number of customers waiting increases. In the third model, FCFS policy is not applied and a scheduling policy is tried to be found out.

Savaşaneril et al. (2010) examine the problem of a manufacturer who jointly accepts customers, quotes lead times and makes inventory decisions. The manufacturer would like to maximize her profit in an environment where there are holding cost for the items left in the inventory and lateness cost for the delayed items. The authors investigate the effect of carrying inventory and different lead time quotation policies on the profit and the effect of base-stock level on the lead time quotation policy. The authors find that the base stock level increases when the precision of the lead time quotation policies decreases. Also, it is shown that an increase in the base stock level does not always lead to a decrease in the number of customers waiting.

Chen and Yu (2005) analyze the value of sharing lead time information in a supply chain consisting of a manufacturer and a customer (inventory manager). The paper discusses two scenarios. In the first scenario, complete information sharing, the customer knows the exact lead time for his orders. The authors show that it is optimal for the inventory manager to adopt a state-dependent, base-stock policy with order-up-to levels depending on the lead time under complete information sharing. In the second scenario, when there is no information sharing, the manufacturer does not share the lead-time information with the customer. Two policies are investigated under this scenario. The first policy is a constant base-stock policy and the second policy is history-dependent base-stock policy. The authors conclude that, under no information sharing scenario, the second policy gives the customer more lead time information than the first policy. The authors also find out that, the value of lead time information increases when the demand is high volume or high variability is observed in the lead time distribution.

Dobson and Pinker (2006) try to determine whether a firm can benefit from sharing state-dependent lead time information. Also, the authors analyze under which conditions, sharing state-dependent lead time information is beneficial for the firm and the customers. To address these two questions, two settings are compared. In the first setting, the firm shares a state-dependent lead time quote with the customers and in the second setting, the firm gives a single lead time for all the customers. The authors show that quoting state-dependent lead times is better than a single lead time quotation policy. Quoting state dependent lead times can increase the throughput of the company while simultaneously reducing the expected waiting time of the customer's in some cases.

Liu et al. (2009) evaluates the value of real time shipment tracking information in a supply chain consisting of a manufacturer and a retailer. A model where the products shipped by the manufacturer pass through serial stages before received by the retailer, is constructed. In this model, each stage represents a physical location. The retailer can have real time information as the products pass through the physical locations. The ordering rule for the retailer is assumed to be order-up-to level for each period obtained by minimizing the one-period expected cost. The authors compare three cases. In the first case, the retailer can access to the real time tracking information. In the second case, the retailer can access to lagged shipment tracking information. In the third case, the retailer cannot access any shipment tracking information. The authors find out that, the long-run average cost of the retailer increases when the tracking information is lagged.

In this study, we try to find the optimal policy and profit for a manufacturer taking production and lead time quotation decisions under both perfect information and imperfect information. We believe that, this is the first study trying to find the optimal policy and profit of a manufacturer taking production and lead time quotation decision under imperfect information.

2.2 Value of Information

There exist many articles studying the value of information in production/inventory management systems. We can differentiate the articles in this stream by flow of information. Two directions are possible for the flow of information. The first direction is from lower echelon to upper echelon. Gavirneni et al. (1999) model the information flow between a supplier and a retailer, where the retailer orders according to an (s, S) policy. The authors confine the study to three models. Under the first model, the base case, the supplier has information only about the past demand data. Under the second model, the partial information sharing, the demand distribution faced by the retailer, the retailer's (s, S) policy and parameters s and S are known by the supplier. Under the third model, complete information sharing the supplier receives immediate information about the retailer's demand in addition to known under the second model. The authors find out that, the information is not beneficial when the end-item demand variance is high, or the difference between S and s is very high or very low. Also, the authors state that the manufacturer does not benefit information when the capacity is low. The authors argue that when the end-item demand variance is moderate and the difference between S and s is not so substantial, and the capacity is high, the benefits of information are great.

Cachon and Fisher (2000) evaluate the value of demand and inventory information in a supply chain consisting of one supplier and N identical retailers. In this study, two levels of information sharing are considered. Under the first one, traditional information sharing, the supplier can only observe the retailers' orders. Under the second one, full information sharing, the supplier can observe retailers' immediate inventory data. The authors believe that under full information sharing, the supplier can improve its both quantity and allocation decisions. However, the authors find limited benefits since the information is most valuable when the retailer is likely to submit an order. The authors think that, the value of information can increase when the demand is unknown.

Simchi-Levi and Zhao (2004) determine the benefit of sharing demand information in a two-stage supply chain, consisting of a capacitated supplier and a retailer, in an infinite horizon. In particular, the authors try to get the optimal policy for the information sharing model, quantify the benefits resulting from information sharing and determine the conditions under which the information is most beneficial for the manufacturer. They show that, a cyclic order-up-to policy, where the manufacturer produces up to the target inventory level as long as there is enough production capacity, is optimal. Also, under both discounted and average cost criterion, the manufacturer's cost decreases due to information sharing when the capacity increases. In addition, under non-stationary demand, the authors observe that information sharing is most beneficial when the demand rate is decreasing and least beneficial when the demand rate is increasing.

The second direction for flow of information is from upper echelon to lower echelon. Ferrer and Ketzenberg (2004) consider a remanufacturing facility where a trade-off between limited information about long supplier lead times and manufacturing yields is faced. The paper analyzes the value of information in two distinct process capabilities; the first one is the ability to obtain purchased parts within a short lead time and the second one is the ability to identify part yield in the disassembly stage of remanufacturing. To analyze the value of information, four different models, where different combinations of two abilities take place, are used. The authors find out that the value of yield information is more valuable than lead time information. Also, the authors argue that having both capabilities is a slightly better having solely the ability of identifying part yield.

He et al. (2002) analyze the value of queue length information in inventory control in a supply chain consisting of a manufacturer and a warehouse.. The concept of information level, where the warehouse manager can get different levels of information; no information, partial information or full information, about the queue length, is used in the study. The authors show that, a warehouse manager can reduce her inventory costs significantly if she switches from no information level to partial information level, under which there is information about whether the manufacturer is busy or available, but no information about the exact queue length. However, in their model, the value of information is not so effective for a warehouse manager switching from partial information to full information.

Bensoussan et al. (2009) determine the value of visibility within a company, where upper stage (production rather than demand) information benefit is assessed. The authors study problem of an inventory manager who cannot observe the current inventory level due to information delays. It is assumed that, the inventory manager uses a reference inventory level, where the most current information is used to when making replenishment decisions. Two information delay types are considered; the one being inventory information delay and the second being demand information delays. The authors demonstrate that the inventory information delay, under which the delays are non-crossing, is a special case of demand information delay. It is found out that a base stock policy is optimal when the replenishment cost is linear. It is also proved that the optimal cost is decreasing with the amount of delay in the system. The authors conclude their studies with a managerial insight; companies having slow-paced information systems should increase their stock levels to compensate for their pace.

In our problem, we consider the flow of information from upper echelon to lower echelon. We assess the value of information by examining a manufacturer under two settings. Under the first setting, the manufacturer faces information distortion whereas under the second setting, the manufacturer takes actions under perfect information. We believe that difference in policies and profits can be used as criteria in determining the value of information.

2.3 Use of Automatic Data Capture Systems

Papers related with the use of automatic data capture systems in production and inventory management is also in the scope of this study.

Lee and Özer (2007) try to analyze the value of RFID implications by different aspects. The authors firstly discusses the potential benefits (labor cost savings, inventory reduction, shrinkage and out-of-stock reduction) that a company can have when RFID is employed. The paper then gives the examples of some ongoing research that incorporate information provided by RFID; value of visibility within a company, value of visibility across companies (downstream information shared upstream and upstream information shared downstream. Under these headings, the authors discusses many models that are not specifically about RFID, but could easily be adapted so that the RFID-benefits can be inferred.

Kök and Shang (2007) consider a single-product, single-location periodic inventory system where the inventory records are not accurate. It is assumed that inaccuracy in inventory changes the physical inventory level but leaves the inventory record unchanged. The authors find a joint inspection and replenishment policy minimizing the total costs (inventory-related and inspection) over a finite horizon. The authors characterize an optimal policy where there exists a threshold inventory level for the inspection decision and base stock for the replenishment decision. Than, they propose a heuristics performing near optimal. The authors find out that, the products having a higher value, larger error variance, lower inspection cost or smaller demand variance should be inspected more frequently than other items. Also, the order-up-to level should be increased when the number of periods since the last inspection increases. Lastly, the costs of proposed heuristics is compared with the optimal costs of a no-error system (such as perfect RFID installed) and found that the proposed heuristic is slightly worse in terms of value of accurate inventory information.

Ferrer et al. (2010) answer the question of how to enhance service quality and what benefits can be reaped by using RFID technology. The paper gives descriptive cases of how to increase capacity, reduce cycle-time, automate processes and enable self-service by adopting RFID.

Lindau and Lumsden (1999) find the effect of automated data capture systems on inventory management by investigating 10 companies adopting these systems. The authors find out that the the higher the technology level of automated data capture system, the better the result.

In our study, the benefits of a RFID system which is used to track the status of production, is determined by examining the policies and profits of a manufacturer under two settings. In the first setting, the manufacturer tracks the status of production via RFID, whereas in the second setting, the manufacturer tracks the status under no RFID system.

CHAPTER 3

MODEL

We consider a joint production and due date quotation problem of a manufacturer in the presence of information distortion. We assume that there exists a single item under consideration. Manufacturer may keep stock to meet demand.

Customers arrive according to a Poisson process with rate λ and they get service on a first come first served (FCFS) basis. The production time is exponentially distributed with parameter μ. A lead time / due date, d, is quoted for each arriving customer. If the customer accepts the quoted lead time, then the customer places an order and waits until the item is available; if he rejects the quoted lead time, he leaves. Customers are assumed to be identical and can place an order one at a time. Order placement does not incur any cost. There is a revenue of R, earned from any customer who has placed an order. The manufacturing facility is assumed to have a single server (machine) and production of an order could be completed later than the quoted lead time. In this case, there is a penalty / lateness cost, ℓ, per item, per unit time charged for the amount of time later than the quoted due date. Apart from quoting a lead time, the manufacturer decides whether to start or continue the production. There is no fixed cost of production. One-for-one replenishment is suitable because there exist a single server queue and no fixed cost of manufacturing. A holding cost, h, is incurred per unit per unit time for the items in inventory. The aim is to find the production and quotation policy that maximizes the profit of the manufacturer.

As mentioned above, a lead time is quoted for the arriving customer and the customer has the flexibility to accept the quoted due date. This flexibility is modeled with an acceptance probability, $f(d)$, in such a way that the customers are more reluctant to accept longer lead times, i.e. $f(d)$ is a decreasing function of d. Moreover, it is assumed that there exists a finite maximum lead time, d_{max}, where $f(d_{max})=0$. Note that a quoted lead time which was rejected by a former customer may be accepted by another one.

The manufacturer takes two decisions as mentioned above. The first one, *acta*, is whether to initiate / continue the production or not. The second one, *actb*, is the lead time quotation. Therefore, an action of the manufacturer can be denoted with a where a=(acta, actb). The action space is defined as $A = Aa \times Ab$ where Aa ={produce, not produce} and Ab = {0, 1, 2,...,d_{max}}.

In the presence of information distortion, there exist two processes that evolve simultaneously; the actual process and the observed process. The actual state of the system is represented by i, whereas the observed state of the system is denoted by i'. The states of the system denote the number of customers waiting in the queue. Both the actual and observed states can take values in S={-∞, …, -1, 0, 1, 2, …, ∞}. The number of items waiting in the inventory is denoted with the negative values of i (and i'), whereas the number of customers in the queue is denoted with the positive values of i

(and i'). The state of the system may change either with the arrival of a customer or arrival of a manufactured part.

In the following sections, firstly we will consider the problem of a manufacturer who can see the actual state of the system completely and present the corresponding model (full information model). Secondly, the problem of a manufacturer under information distortion will be examined. Under information distortion, two approaches will be discussed. First, the model that solves the problem to optimality will be given. Then a heuristic approach will be presented.

3.1 Full Information Model

In this section, we consider a manufacturer who does not face any information distortion in the process. The manufacturer can perfectly see which state the system is actually in and hence the actions are taken accordingly. The state of the system will be represented by i. Under the assumption of Poisson arrivals and exponential production times, the process is a Continuous Time Markov Chain. By applying uniformization ("the technique of uniformizing the rate in which a transition occurs from each state by introducing transitions from a state to itself", (Ross, 1996)), the Continuous Time Markov Chain is transformed to an equivalent discrete time model. The problem is formulated as a Markov Decision Process (MDP). Note that, during the analysis only stationary policies will be considered.

Lead time quotation is made upon only customer arrival. Production decision, on the other hand, is taken at any point in time including customer arrival, part arrival and fictitious part arrival. Therefore, the *decision epochs* are determined not only by customer arrivals but also by part arrivals and fictitious part arrivals. Note that a *transition* is defined by a customer arrival, a part arrival (i.e, production completion), or a fictitious part arrival.

Under the actions explained above, the transition probabilities are as follows:

i. Under "produce" action given that an arriving customer is quoted d;

$$p(j \mid i, a) = \begin{cases} \frac{\lambda}{\lambda+\mu} f(d) & j = i+1 \\ \frac{\lambda}{\lambda+\mu}(1-f(d)) & j = i \\ \frac{\mu}{\lambda+\mu} & j = i-1 \\ 0 & otherwise \end{cases} \tag{3.1}$$

ii. Under "do not produce" action, given that an arriving customer is quoted d;

$$p(j \mid i, a) = \begin{cases} \frac{\lambda}{\lambda+\mu} f(d) & j = i+1 \\ 1-\frac{\lambda}{\lambda+\mu} f(d) & j = i \\ 0 & otherwise \end{cases} \tag{3.2}$$

Under full information under the average reward criterion the optimality equation is as follows:

$$g + v^*(i) = \frac{-h(i^-)}{\lambda + \mu} + \frac{\lambda}{\lambda + \mu} \tau_1 v^*(i) + \frac{\mu}{\lambda + \mu} \tau_2 v^*(i) \qquad \textbf{(3.3)}$$

Where operators τ_i are defined as

$$\tau_1 v^*(i) \equiv \max_d \begin{Bmatrix} (R - \ell L_i(d) + v^*(i+1)) f(d) + (1 - f(d)) v^*(i) & for\ i \geq 0 \\ (R + v^*(i+1) f(d) + (1 - f(d)) v^*(i) & for\ i < 0 \end{Bmatrix} \qquad \textbf{(3.4)}$$

and

$$\tau_2 v^*(i) \equiv \max \begin{Bmatrix} v^*(i), v^*(i-1) & for\ i \leq 0 \\ v^*(i-1) & for\ i > 0 \end{Bmatrix} \qquad \textbf{(3.5)}$$

In Equation (3.3), g represents the long-run optimal average profit per transition, $v^*(i)$ stands for the relative effect of starting in state i on the total expected reward under the optimal policy. The holding cost until the next transition is given by;

$$\frac{-h(i^-)}{\lambda + \mu} \qquad \textbf{(3.6)}$$

where i^- = max {- i, 0}. If a customer arrives in state i and a lead time of d is quoted, then the expected profit will be given by $(R - \ell L_i(d)) f(d)$. $L_i(d)$

denotes the expected amount of delay for a customer arriving in state i and quoted the lead time d. Under the FCFS policy it is computed as;

$$L_i(d) = \int_d^{\infty} (x-d)E_{i+1}(x)dx, \quad if\,(i \geq 0);$$
$$L_i(d) = 0, \quad if\,(i < 0); \tag{3.7}$$

where $\begin{cases} E_{i+1}(x) = \dfrac{\mu(\mu x)^{j-1}}{(j-1)!} e^{-\mu x}, & if\;\; x \geq 0 \\ 0 & otherwise \end{cases}$

Note that no lateness cost incurs when there is inventory on hand.

For this problem, the following equivalent linear programming model is introduced:

$$\begin{aligned} (Pfull) \quad & \max \sum_i \sum_a r_{ia}\, \pi_{ia} \\ & subject\ to \\ & (1) \quad \sum_a \pi_{ja} - \sum_i \sum_a \pi_{ia}\, p(j \mid i,a) = 0 \qquad \forall j \\ & (2) \quad \sum_i \sum_a \pi_{ia} = 1 \\ & (3) \quad \pi_{ia} \geq 0 \qquad \forall i,a \end{aligned}$$

Model 3.1 – Full Information Model

In this formulation, r_{ia} denotes the expected one-step reward when the actual state is i and action a is taken. π_{ia} denotes the long-run fraction of time at which the system is in state i and action a is taken. As mentioned above, a stands for both production and quotation actions.

The profit obtained in state i under the action a, i.e. r_{ia}, until the next transition is as follows:

$$r_{ia} = \frac{h\, i^{-}}{\lambda + \mu} + \frac{\lambda}{\lambda + \mu}(R - \ell\, L_i(d))\, f(d) \quad for\ \forall\, i \tag{3.8}$$

3.2 Partial Information Model

In this section, the problem of the manufacturer in the presence of information distortion is examined. As mentioned, under information distortion there exist two processes; actual process and observed process. The manufacturer cannot see the states of the actual process, but he can see the states of the observed process. The manufacturer observes the state and holds an opinion which actual state the system is in. Hence, the manufacturer has partial information about the actual state. Then, the manufacturer decides which actions to take. Note that, the actions control both the observed and actual processes. The system is observed again after the transition occurs under the manufacturer's actions.

Under partial information, when the actual state is i, the manufacturer takes the signal that it is i', with a known probability $O(i'|i)$. Therefore, the manufacturer has perfect information on the observed process and partial information (information distortion) on the actual process. Note that the SxS matrix formed by the $O(i'|i)$ entries will be called *observation matrix* throughout the text. Under information distortion, the state of the system can be represented by (i, i').

Under the assumption of Poisson arrivals and exponential production times, the problem under consideration can be modeled as POMDP. Note that, during the analyses not only stationary but also randomized policies will be considered.

As in full information model, lead time quotation is made only upon customer arrival. It is assumed that production decision can be taken upon customer or part arrivals, or fictitious part arrivals.

Under the actions explained above, the transitions probabilities are as follows:

i. Under production action, given that an arriving customer is quoted d;

$$p(j, j' \mid i, i', a) = \begin{cases} \dfrac{\lambda}{\lambda+\mu} f(d) O(j' \mid j) & j = i+1 \\ \dfrac{\lambda}{\lambda+\mu} (1 - f(d)) O(j' \mid j) & j = i \\ \dfrac{\mu}{\lambda+\mu} O(j' \mid j) & j = i-1 \\ 0 & \textit{otherwise} \end{cases} \qquad \textbf{(3.9)}$$

ii. Under "do not produce" action, given that an arriving customer is quoted d;

$$p(j,j'|i,i',a)=\begin{cases}\frac{\lambda}{\lambda+\mu}f(d)O(j'|j) & j=i+1\\ 1-\frac{\lambda}{\lambda+\mu}f(d)O(j'|j) & j=i\\ 0 & otherwise\end{cases} \quad \textbf{(3.10)}$$

The difference between full information model and partial information model is that; the latter is one constrained in action space in the sense that same actions must be taken under the same observed state whatever the actual state is.

3.2.1 Optimal Policy under Partial Information

To obtain an optimal solution to the problem given above, we need to introduce constraints to the full information model to make sure that the manufacturer takes the same actions in the observed state i'. The following constraints are added into *(Pfull)* in order to find an optimal solution under partial information. As mentioned the state of the system is represented by (i, i'). Then the following constraints must be satisfied:

$$\alpha_{i'a}=\frac{\pi_{ii'a}}{\sum_b \pi_{ii'b}} \qquad \textit{for all } a\in A,\ i,i'\in S \quad \textbf{(3.11)}$$

where $\pi_{ii'a}$ denotes the long run fraction of time when the actual state is i, observed state is i' and action a is taken.

However, $\alpha_{i'a}$ for $a \in A$ and $i' \in S$ are unknowns. Note that, introducing (3.11) into the full information model results in a nonlinear model. Before presenting the model, we make the following transformation;

$$\pi_{ii'} = \sum_{b \in A} \pi_{ii'a} \qquad \textit{for all } i, i' \in S \tag{3.12}$$

Hence, $\pi_{ii'a} = \alpha_{i'a}\pi_{ii'}$ *for* $i, i' \in S, a \in A$. The optimal model under partial information is as follows:

$$(Ppartial) \quad \max \sum_{i} \sum_{i'} \sum_{a} r_{ii'a}\, \pi_{ii'} \alpha_{i'a}$$

subject to

$$(1) \qquad \pi_{jj'} - \sum_{i} \sum_{i'} \sum_{a} \pi_{ii'}\, \alpha_{i'a}\, p(j, j' \mid i, i' a) = 0 \qquad \forall\, j, j' \in S$$

$$(2) \qquad \sum_{i} \sum_{i'} \pi_{ii'} = 1$$

$$(3) \qquad \sum_{a} \alpha_{i'a} = 1 \qquad \forall\, i' \in S$$

$$(4) \qquad \alpha_{i'a} \geq 0 \qquad \forall\, i' \in S,\ \forall\, a \in S$$

$$(5) \qquad \pi_{ii'} \geq 0 \qquad \forall i, i' \in S$$

Model 3.2 – Partial Information Model

Note that, the one-step rewards under full information and partial information are same, i.e. $r_{ii'a} = r_{ia}$. The reason is that, the revenues are earned and the costs are incurred according to the actual process, and not according to the observed one under partial information. $\pi_{ii'}$ denotes the long-run fraction of time at which the system is in actual state i and observed state i'. For a similar analysis of POMDP, see Serin and Kulkarni (2005).

3.2.2 Heuristic Policy

In section 3.2.1, we consider a manufacturer taking decisions under information distortion and present a nonlinear model to find the optimal policy. Since the presented model is a nonlinear one, it is hard to reach an optimal solution in a reasonably short time. Therefore, to obtain the optimal solution in a reasonably short time, we introduce a heuristic policy, which is based on a linear programming model.

The nonlinear model given in section 3.2.1 is obtained by introducing nonlinear constraints to the full information model. A heuristic policy can be obtained by removing the constraints under partial information while defining the state as (i, i'). Note that removing the constraints will result in a deterministic policy in actual state i.

In section 3.2.1 the manufacturer is forced to take the same actions in state i'. On the contrary, in this section, the constraint of taking the same decision in state i' is first removed, and then introduced; i.e., a sequential approach is developed. This sequential approach leads to a randomized policy in i', described as follows.

Under information distortion, the manufacturer is not certain about the actual state i. Yet, the manufacturer holds an opinion on the actual state i when observing state i', due to $O(i'|i)$. Therefore, the manufacturer can take optimal actions of the actual state i for the observed state i' with a probability $O(i'|i)$.

Removing the constraints causing nonlinearity in *(Ppartial)* will result in the following model:

$$
\begin{aligned}
&(Pheuristic) \quad \max \sum_{i} \sum_{i'} \sum_{a} r_{ia}\, \pi_{ii'a} \\
&\quad\quad \textit{subject to} \\
&\quad\quad (1) \quad \sum_{a} \pi_{jj'a} - \sum_{i} \sum_{i'} \sum_{a} \pi_{ii'a}\, p(j, j' \mid i, i'a) = 0 \qquad \forall j, j' \in S \\
&\quad\quad (2) \quad \sum_{i} \sum_{i'} \sum_{a} \pi_{ii'a} = 1 \\
&\quad\quad (3) \quad \pi_{ii'a} \geq 0 \qquad \forall i, i' \in S,\ \forall a \in A
\end{aligned}
$$

Model 3.3 – Heuristic Model

Note that, under this model, the profit earned is same with the profit obtained under *(Pfull)*, because the manufacturer takes actions for the observed state *i'* based on the actual state *i*.

Proposition 1*: Steady state probability of* $\pi_{ii'a}$ *under (Pheuristic) and steady state probability of* π_{ia} *under (Pfull) are related as follows:*

$$\pi_{ii'a} = \pi_{ia}\, O(i' \mid i) \tag{3.13}$$

Proof: *Firstly note that, the following relationship can be written by using the first constraint of (Pheuristic);*

$$\sum_{b} \pi_{jj'b} = \sum_{i} \sum_{i'} \sum_{a} \pi_{ii'a}\, p(j, j' \mid i, i'a) \qquad \forall j, j' \in S \tag{3.14}$$

where $p(j,j'|i,i'a)$ *is defined in Equations (3.9) and (3.10). Note that*

$$p(j,j'|i,i'a) = p(j|i,a)O(j'|j) \qquad \textbf{(3.15)}$$

from Equations (3.1) and (3.2). Hence by using Equation (3.15), Equation (3.14) can be expressed as follows;

$$\sum_{b}\pi_{jj'b} = \sum_{i}\sum_{i'}\sum_{a}\pi_{ii'a}\ p(j|i,a)O(j'|j) \qquad \textbf{(3.16)}$$

Assume that Equation (3.13) holds. Then, Equation (3.16) can be written as;

$$\sum_{b}\pi_{jb}\,O(j'|j) = \sum_{i}\sum_{i'}\sum_{a}\pi_{ia}\ O(i'|i)\,p(j|i,a)O(j'|j) \qquad \forall j,j' \in S \qquad \textbf{(3.17)}$$

$$\Rightarrow \sum_{b}\pi_{jb}\,O(j'|j) = \sum_{i}\sum_{a}\pi_{ia}\ p(j|i,a)O(j'|j) \qquad \textbf{(3.18)}$$

Note that, in Equation (3.18) $O(j'|j)$*'s cancel out. Hence,*

$$\Rightarrow \sum_{b}\pi_{jb} = \sum_{i}\sum_{a}\pi_{ia}\ p(j|i,a) \qquad \textbf{(3.19)}$$

■

Using the solution of *(Pheuristic)*, we can derive a possibly randomized policy depending on the observed states. To do so, firstly we define the following probabilities:

$$\beta(a \mid i') = \frac{\sum_{i} \pi_{ii'a}}{\sum_{i} \sum_{b} \pi_{ii'b}} \qquad \textit{for all } a \in A,\ i, i' \in S \tag{3.20}$$

$\beta(a \mid i')$ denotes the probability that action a is taken given that the observed state is i'.

A heuristic policy is constructed on $\beta(a \mid i')$ by taking action a with probability $\beta(a \mid i')$ whenever the system is at state (i, i'). Thus the heuristic policy naively tries to mimic the policy under full information.

Note that under the given heuristic policy, the transition probabilities can be expressed as:

$$p(j, j' \mid i, i') = \sum_{a} p(j \mid i, a)\, \beta(a \mid i')\, O(j' \mid j) \tag{3.21}$$

By using these transition probabilities, we can evaluate the heuristic policy by solving the system of equations given below:

$$\pi_{jj'} - \sum_{i} \sum_{i'} \pi_{ii'}\, p(j, j' \mid i, i') = 0 \qquad \forall j, j' \in S \tag{3.22}$$

$$\sum_{i} \sum_{i'} \pi_{ii'} = 1 \tag{3.23}$$

To calculate the profit under this heuristic policy, the following equation is employed;

$$\sum_{i}\sum_{i'} r_{ii'}\,\pi_{ii'} \qquad \textbf{(3.24)}$$

In the above equation, $r_{ii'}$ denotes the one step reward when the actual state is i and the observed state is i'. Note that, under heuristic policy, the costs are incurred and profits are earned according to actual process. Therefore, $r_{ii'}$ can be expressed as:

$$r_{ii'} = \sum_{a} r_{ia}\,\beta(a\,|\,i') \qquad \textbf{(3.25)}$$

3.2.3 An Example

In this section, an example will be given in order to see the effects of information distortion on policies and profits. Two settings will be considered. Under the first setting, the manufacturer perfectly sees the actual states and takes the optimal actions under full information. Under the second setting, the manufacturer imperfectly observes the actual states, .i.e. she faces with information distortion. Under the second setting, firstly the manufacturer pursues optimal policy under information distortion. Secondly, the manufacturer carries out heuristic policy under information distortion.

Throughout the text, due date policies are denoted as an array of state - due date pairs. Take the case of (-2, 0). “-2” denotes two units of stock, “0” denotes the quoted lead time. Another instance may be (2, 3). In this case, the customer arriving to join the queue for the second place will be quoted a lead time of "3".

The parameters for the three manufacturers are as follows: R=5, ℓ=2, $\boldsymbol{\lambda}$=0.35, h= 0.60 and *A={produce, do not produce} x {0, 1, 2, 3, 4, 5}*. When "5" is quoted, an arriving customer will not accept the quoted lead time, i.e. $f(d_{max}) = 0$.

Under the first setting, the manufacturer has a base stock level of 1 unit, and starts rejecting when the number of customers waiting is 5. The quotes are as [(-1, 0); (0, 1); (1, 2); (2, 3); (3, 3); (4, 4); (5, 5)]. The profit for this policy is 0.83543772.

Note that, information distortion should be clarified before giving the second setting. For this example assume that, when the actual state is i, the manufacturer can observe the states (i+1, i, i-1) with probabilities O(i+1|i), O(i|i) and O(i-1|i), respectively. The policies of the second and third settings will be examined under the following observation probabilities (0.25, 0.50, 0.25).

The manufacturer following the optimal policy under information distortion has a base stock level of 2 units, starts rejecting when the number of customers waiting reaches 6. The quotes are [(-2, 0); (-1, 0); (0, 1); (1, 1); (2, 2); (3, 3); (4, 4); (5, 4); (6, 5)]. Note that, the optimal policy under partial information is not randomized for this specific instance. The profit generated under optimal policy is 0.75629761. The manufacturer following optimal policy has a higher base stock level than under first setting. Also, shorter lead times are quoted. Hence, the profit earned is lower than under the first setting.

The manufacturer adopting the heuristic policy under information distortion has a base stock level of 3 units. Rejecting the customer starts when the number of customers waiting is 7. As opposed to the full information policy and optimal policy, the actions are randomized. Therefore, the quotes under this setting will be given with the probability of taking that action. The following notation will be used for the quotes: (-1, 1;0.851). The last term represent the probability of quoting "1" when the observed state is "-1". By using this notation, the quotes are as follows: [(-3, 0 ; 1); (-2, 0 ; 1); (-1, 0 ; 0.851); (-1, 1 ; 0.149); (0, 0 ; 0.556); (0, 1 ; 0.389); (0, 2 ; 0.055); (1, 1 ; 0.618); (1, 2 ; 0.346); (1, 3 ; 0.036); (2, 2 ; 0.690); (2, 3 ; 0.310); (3,3 ; 0.985); (3, 4 ; 0.015); (4, 3 ; 0.781); (4, 4 ; 0.219); (4, 5 ; 0.008); (5, 4 ; 0.877); (5, 5 ; 0.123); (6, 5 ; 1); (7, 5 ; 1). The profit under this setting is 0.66307105. Note that the highest base stock level is attained under this setting. Moreover, the highest number of customers waiting is reached under this policy. All of these are consequences of taking randomized actions under the heuristic policy. As expected, the lowest profit is earned under this setting.

CHAPTER 4

NUMERICAL ANALYSIS

In this chapter the effect of information distortion (information availability) on the policies and profits is analyzed. Firstly, the effect of information distortion is examined under different parameters. Both heuristic and optimal policies obtained by the methods given in Chapter 3 are discussed. The profit gap between the two policies is investigated. The effect of observation matrix on the information distortion is also assessed. The effect of Make-to-Order (MTO) (where the base stock level is zero) and Make-to-Stock (MTS) (where the optimal base stock level is kept) schemes on the value of information is analyzed. Finally, different lead time quotation policies; accept-all, accept-reject and precise lead time; are compared to find under which policy the value of information is highest.

Firstly, information distortion should be clarified. Although it can be defined in many different ways, two specific structures with respect to the observation matrix are investigated under different parameters. In the first structure, given that the system is in state i, it is possible to observe the system in states (i-1, i, i+1) with probabilities (O_{ii-1}, O_{ii}, O_{ii+1}). We call this *triple state observation*. Under the second structure, it is assumed that given that the system is in state i, states (i-1, i) [or (i+1, i)] can be observed with probability (O_{ii-1}, O_{ii}). [or (O_{ii+1}, O_{ii})]. We call this *double-state observation*. The first structure for double-state observation will be abbreviated as "DSOF"

(Double State Observation Former) whereas the second will be abbreviated as "DSOL" (Double State Observation Latter). Note that, under both double-state and triple-state observation structures, it is possible to observe state i, when the actual state is i with probability O_{ii}. O_{ii} will be called self-state observation probability throughout the text.

To perform the analysis, a workstation having a RAM of 4 GB and a processor of Intel Core I7 620M with 2.67 GHz is employed. The models given in Chapter 3 are run in GAMS program. BARON is chosen as the solver for optimal policies under the partial information, whereas CPLEX is preferred for full information policies and heuristic policies. The inputs for the models; profits and transition probabilities; are calculated by running Dev C++ compiler. Note that, finding the full information optimal and heuristic policies requires negligible time compared with optimal policies under partial information. 878 cases were analyzed in this study.

In the analysis, the profit gap between the optimal and heuristic policies and the policy under full information is used as a performance measure. Specifically the following measures are used;

$$GAP_{opt-heu} = \frac{\text{Profit}_{\text{opt}} - \text{Profit}_{\text{heu}}}{\text{Profit}_{\text{opt}}} \tag{4.1}$$

$$GAP_{full-heu} = \frac{\text{Profit}_{\text{full}} - \text{Profit}_{\text{heu}}}{\text{Profit}_{\text{full}}} \tag{4.2}$$

$$GAP_{full-opt} = \frac{\text{Profit}_{\text{full}} - \text{Profit}_{\text{opt}}}{\text{Profit}_{\text{full}}} \tag{4.3}$$

In the above equations, "Profit_{opt}" and "Profit_{heu}" represent the profit under partial information for optimal and heuristic policies, respectively. The profit under full information is represented by "Profit_{full}".

For all the analysis, the following parameters are used: R=5, ℓ=2, μ=1. The production action space is Aa={produce, do not produce}. Action space for lead time quotation is assumed as Ab={0, 1, 2, 3, 4, 5} for sections 4.1 - 4.3. In section 4.4, we assume Ab can take different values. In all the figures the action space for production will be abbreviated as Aa={p, dp}

The acceptance probability of customers is assumed as;

$$f(d) = 1 - \frac{d}{d_{\max}} \tag{4.4}$$

4.1 Analysis of Heuristic and Optimal Policies under Partial Information in the Presence of Triple-State Observation

In this section, heuristic and optimal partial information profits for triple-state observation are compared under different parameters to see the effect of information distortion on the performances. Specifically the effect of observation matrix on the profits is analyzed and the value of information is assessed.

As mentioned above, under triple state observation, given that the system is in i, three states; i, i-1, i+1, can be observed with probabilities O_{ii}, O_{ii-1},

O_{ii+1}, respectively. It is assumed the probability of observing states *i*-1 and *i*+1 are equal; that is,

$$O_{ii-1} = O_{ii+1} = 1 - {O_{ii}}/{2} \qquad \textbf{(4.5)}$$

For example, when O_{ii}=0.40, O_{ii-1}=O_{ii+1}=0.30. In this case, it is more likely to observe the self–state than to observe O_{ii-1} or O_{ii+1}.

4.1.1 The effect of unit holding cost on value of information

Firstly, profit under optimal policy under partial information will be discussed under different holding cost values. The profits earned under optimal policy for increasing holding cost values are shown in Figure 4.1.

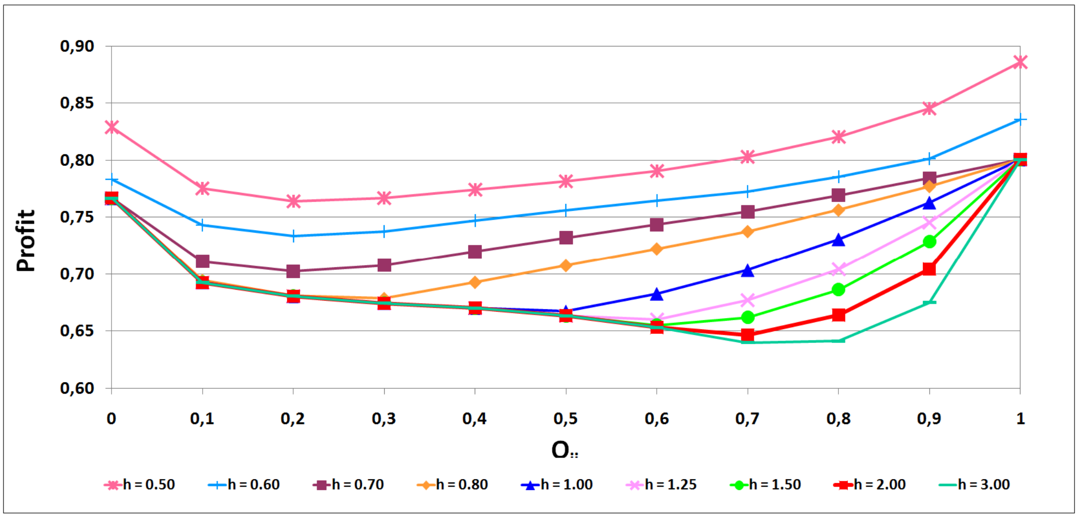

Figure 4.1 - Profits generated by optimal policies under different holding costs vs. O_{ii} under triple state observation under R=5, ℓ=2, λ=0.35 and A={p,dp}×{0,1,…,5}

Observation 1-a: *An increase in self-state observation probability does not necessarily increase the profit, i.e. it may imply higher information distortion.*

First of all, self–state observation probability giving the lowest profit can be interpreted as the probability value under which the value of information is highest. Under different parameters, the lowest profit is realized under different self-state probabilities. One would expect to see, as O_{ii} increases from 0 to 1, the policy and profit would approach to those obtained under full information model. However, this is not the case for triple-state observation (also for double state). For holding cost values shown in Figure 4.1, the lowest profit is yielded under O_{ii} values greater than 0. The analysis shows that if self-state observation probability is low, then an increase in O_{ii} does not necessarily imply information availability (or equivalently it does not imply less information distortion), i.e. the value of information can increase. Under all holding cost values in Figure 4.1 as self–state observation probability increases, the profit under optimal policies first falls and then increases. Take the case under h=0.60. For O_{ii} values less than 0.20, the optimal policy quotes positive lead times even if there are items in stock, i.e. the policy reserves the item to deliver to the same customer at a later time. This is not a rational policy because it may lead to unnecessary loss of customers and revenue. Furthermore, losing a customer results in unnecessary holding cost. As a result, lower profit than the one under full information policy is earned. Under h=0.6, for $O_{ii} \in [0, 0.20]$ the highest profit is generated under O_{ii}=0.00. The reason is as follows. Note for instance that, when optimal base stock level is 1, under O_{ii}=0.00 when the observed number of stock is 1, the manufacturer has no doubt that actual stock level is 0. Therefore, although observed stock level is positive, quoting positive lead times seems reasonable. On the other hand, for O_{ii} values greater than 0, an observed stock level may correspond to several (actual) stock levels. When the observed stock level is 1, the actual stock level could indeed be 1. Thus, it is more likely that quoting positive lead times is an irrational policy. The higher the O_{ii} value, the more irrational the policy is and the lower the profit. In conclusion, for $O_{ii} \in [0, 0.2]$, when $O_{ii} = 0.00$, information distortion is relatively the lowest.

Under the same holding cost (h=0.6), for O_{ii} values greater than 0.20, the lead time quote is zero when the manufacturer has items in inventory, i.e. the policy is partly in line with the policy under full information. Hence unnecessary loss of customers and revenue is avoided. However, there are slight variances in terms of duedate quotes, especially for middle values of O_{ii} ($O_{ii} \in [0.3, 0.6]$). When policies are analyzed under h=0.60, for O_{ii} less than 0.6, it is seen that the lead time quotes are deterministic but shorter than the quotes under full information policy. Therefore, additional penalty cost is incurred. The profit under O_{ii}=0.30 takes the lowest value for $O_{ii} \in [0.3, 0.6]$, since the shortest lead times are quoted under O_{ii}=0.30. As O_{ii} increases, the lead times get closer to the ones under the full information policy. Hence, less penalty cost is incurred and the profit increases. For O_{ii} values greater than 0.60, as O_{ii} gets closer to 1, the policies becomes randomized. A lead time quotation policy similar to the full information lead time policy is pursued for O_{ii} values greater than 0.70, but because of the randomization the profits are lower than the full information profit. The lowest profit is yielded under O_{ii}=0.70 in (0.70, 1.00) since the shortest lead times, are quoted under O_{ii}=0.70. In summary, for O_{ii} values greater than 0.20, lead times are shorter than those under full information. But as O_{ii} increases, the quotation policy approaches to full information policy, i.e. longer lead times are quoted.

Observation 1-b: *Under make-to-order production scheme, for O_{ii} values where the information distortion is highest, the optimal decision is to keep stock, and the higher the cost of keeping stock, the higher the value of information.*

Under sufficiently high holding cost ($h \geq 0.7$), the system operates under the make-to-order scheme under full information. In that case a change in holding cost does not affect the profit. In Figure 4.1, it is observed that if O_{ii} is sufficiently low, and holding cost is sufficiently high (for example when $O_{ii} \in [0, 0.2]$ and $h \in \{1.00, 1.25, 1.50, 2.00, 3.00\}$, or equivalently, when $O_{ii} \leq 0.2$ and $h \geq 1.00\}$), still MTO scheme is the optimal operating scheme. Therefore, an increase in holding cost does not affect the profit.

On the other hand, as O_{ii} increases, the system switches to a hybrid MTS-MTO scheme and starts keeping stock (for example, $O_{ii} \geq 0.5$ and $h \in \{1.00, 1.25, 1.50, 2.00, 3.00\}$). When the system keeps stock under partial information, an increase in holding cost decreases the profit.

The reason for operating under MTO for low O_{ii} and under MTS for higher O_{ii} is as follows. Consider the extreme case where O_{ii}=0. When the manufacturer observes that there are no customers in the system, he perfectly knows that there exists 1 customer in the system and makes the quotes accordingly. Since customer arrival rates are relatively low (hence this leads to MTO), the perfect information in state 0 is quite useful. Hence, the system does not keep stock similar to the full information case, whereas the profit obtained is slightly lower than the profit under full information. As O_{ii} increases (but still low) the amount of information provided decreases, but it is still sufficient so that the system still operates under MTO. As O_{ii} increases, the lead time quotes are less accurate: a short quote might be stated when there is actually relatively higher number of customers waiting.

As O_{ii} increases, the information distortion also increases and there exists a threshold at which the system starts keeping 1 unit of stock, due to not being able to see the actual number of customers in the system. Keeping stock dampens the effect of wrong due-date quotation. Note that, the value at which the system starts keeping stock increases with h value. If the system operates under MTO scheme, the O_{ii} value under which the profit is lowest is as high as 0.70. For $O_{ii} \in [0, 0.7]$, as O_{ii} increases the effect of wrong due date quotation increase. It is possible to dampen the effect by keeping stock; however this option results in holding cost. As h increases, the O_{ii} value at which the system starts keeping stock increases. Note that, when stock is kept, the system may irrationally quote positive lead times when there is an item in stock. But, this behavior vanishes as O_{ii} further increases and as a result the profit increases. When O_{ii} is sufficiently high, the information level is high enough that the operating scheme is MTO again. □

4.1.2 The effect of arrival rate on value of information

Behavior of the profits with respect to O_{ii} under varying customer arrival rates by optimal policies is shown in Figure 4.2.

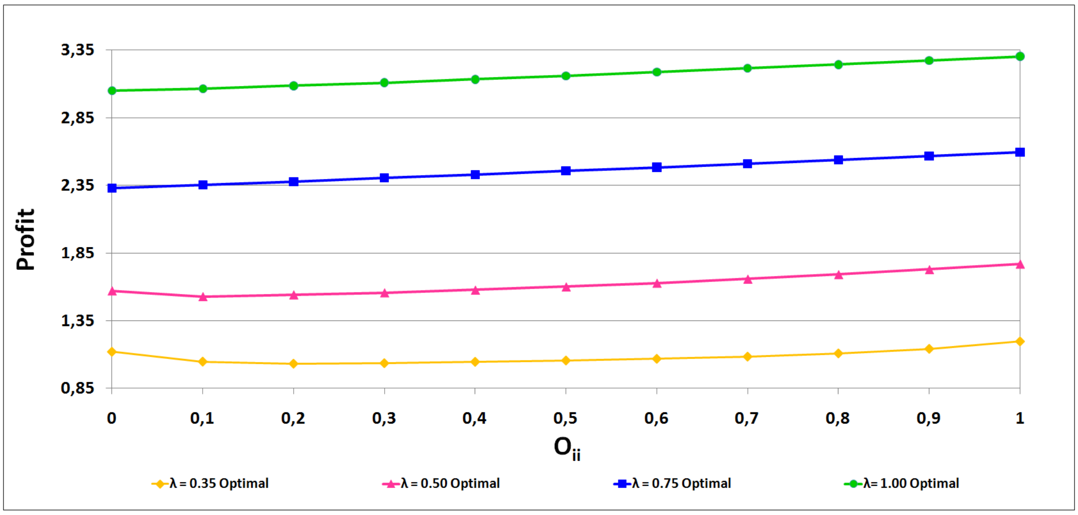

Figure 4.2 - Profits earned by optimal policies under different customer arrival rates vs. O_{ii} under triple state observation under R=5, ℓ=2, h=0.50 and A={p,dp}×{0,1,…,5}

Note that, under different customer arrival rates, the comparison of profit per unit transition is not meaningful as the rate changes with the arrival rate. Hence, when comparing customer arrival rates, the calculations are based on profit per unit time, not per transition.

Observation 2: *As customer arrival rate increases, the O_{ii} value where the value of information is highest decreases.*

As shown in Figure 4.2, as customer arrival rate increases, the O_{ii} value where the value of information is highest has a tendency to decrease. For relatively low customer arrival rates, $\boldsymbol{\lambda}$=0.35 and $\boldsymbol{\lambda}$=0.50, the highest benefit of information is obtained under O_{ii}=0.20 and O_{ii}=0.10 respectively, whereas for high customer arrival rates, $\boldsymbol{\lambda}$=0.75 and $\boldsymbol{\lambda}$=1.00, the highest benefit of information is obtained under O_{ii}=0.00.

When λ is low, as discussed in Observation 1-a, for low O_{ii} values an increase in O_{ii} results in a decrease in profit (i.e, an increase in the value of information). The reason for decrease in profit is irrationally quoting positive lead times when there is stock. For very low O_{ii} values, quoting positive lead times is actually the right action, since an observed positive stock corresponds to an out-of-stock situation. As O_{ii} increases, it is less certain whether an observed stock corresponds to an item or out-of-stock situation, and thus the profit decreases. As arrival rate increases, so does the optimal stock level (under full information). When O_{ii}=0, when one unit of stock is observed, possibly there are two units in stock or no units at all. Thus, low O_{ii} values do not necessarily correspond to improved information availability. Therefore, as O_{ii} increases, information availability increases together with the profit. □

4.1.3 Comparison of the heuristic policy with the optimal policy

Heuristic policy is more inflexible in nature in contrast to the optimal policy. The inflexibility of the heuristic policy may lead to considerable declines in profits especially under high holding cost values. Figure 4.3 shows the profits under heuristic policy under different holding cost values.

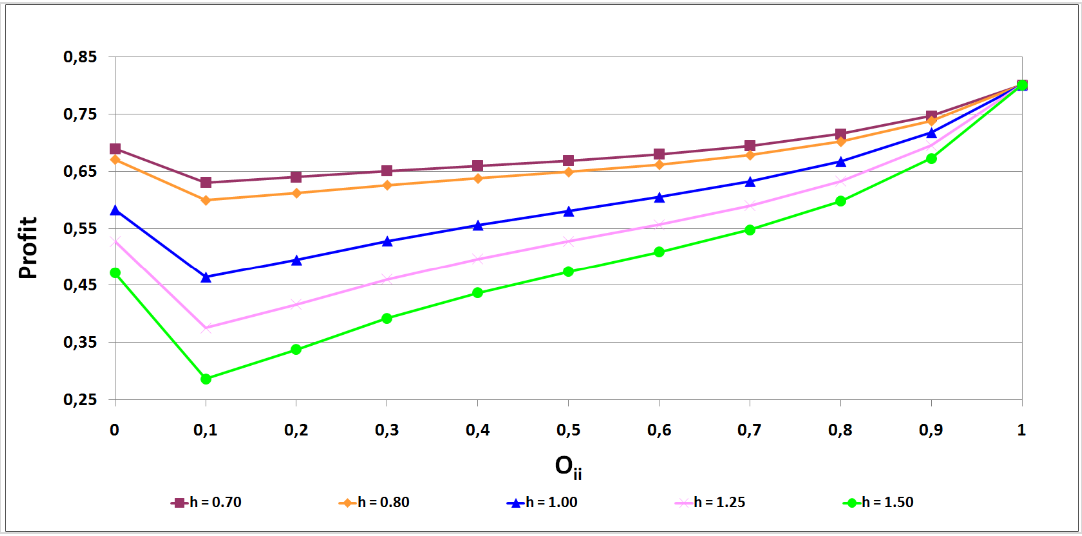

Figure 4.3 - Profits obtained by heuristic policies under different holding costs vs. O_{ii} under triple state observation under R=5, ℓ=2, λ=0.35 and A={p,dp}×{0,1,…,5}

For all the holding cost values in Figure 4.3, a decline in the profits is seen as O_{ii} increases from 0.00 to 0.10. The reason for the decline in the profit is the addition of an observable state. Under heuristic policy, as O_{ii} increases from 0.00 to 0.10, the number of randomized actions increases. Under

O_{ii}=0.00, when the manufacturer observes state i, the actual state will be either i-1 or i+1. On the other hand, under O_{ii}=0.10, when the manufacturer observes state i, the actual state can be i-1, i, or i+1. Therefore, the randomization in actions increases when O_{ii} increases from 0.00 to 0.10. The increase in the number of randomized actions also increases the value of information.

In Figure 4.3, for O_{ii} values greater than 0.10, as the self-state observation probability increases, the value of information decreases. The reason is as follows. Under the same full information policy, for all the self-state observation probabilities (except O_{ii}=0.00 and O_{ii}=1.00), the same actions are taken with changing probabilities under heuristic policy. In other words, the structure of the heuristic policy is same under the same full information policy. First of all, due to randomization a higher base stock level than full information base stock level is compulsory. Secondly, positive lead times are quoted when there are items in the inventory. Thirdly, lead times are randomized. As O_{ii} increases, nothing improves in the policy. However, with an increased self-state observation probability, heuristic policy can mimic the full information policy more accurately. For instance, as O_{ii} increases, the heuristic model decreases the long run fraction of time spent in the adopted base stock level (which is higher than full information base stock level). Therefore the value of information decreases with increasing O_{ii} values.

Observation 3*: Under partial information, optimal policy is more robust to the changes in self–state observation probability than the heuristic policy.*

Heuristic policy is very much dependent on full information policy by definition, and differs from the full information policy only slightly as self–state observation probability changes. In other words, it cannot adapt itself as O_{ii} increases. On the contrary, optimal policy distinguishes itself by adapting to the changes in O_{ii}. It is flexible enough to respond to the changes in self–state observation probability by quoting positive lead times when there are items in the inventory, quoting shorter lead times than full information policy and adopting randomized actions. As the self-state observation probability increases, the optimal policy may change the action, i.e. not necessarily the same action is taken for the observed state i' for changing O_{ii} values. Hence, the negative effect of information distortion is minimized under this policy. □

To sum up, optimal policies has the flexibility to switch actions as the self–state observation increases. However, policy is same under heuristic policy for all O_{ii} values. In other words, the heuristic policies are insensitive to changes in self–state observation probability.

Observation 4: *Given that the system operates under the same policy under full information, as holding cost increases, the profit gap between the heuristic and optimal policies increases under the same self–state observation probability.*

Under partial information, the holding cost is higher due to having a higher base stock level than full information policy, reserving items to deliver at a later time and due to randomized lead times. As mentioned, heuristic policy takes the same actions for the observed state *i'* for changing O_{ii} values under the same full information policy. Therefore, under the same full information policy, a fall in the profits generated under heuristic policy is triggered by the increase in the holding cost. However, if the increase in the holding cost changes the policy obtained under full information (by decreasing the stock level), the increase in holding cost does not necessarily increase the gap between profits under optimal and heuristic policies.

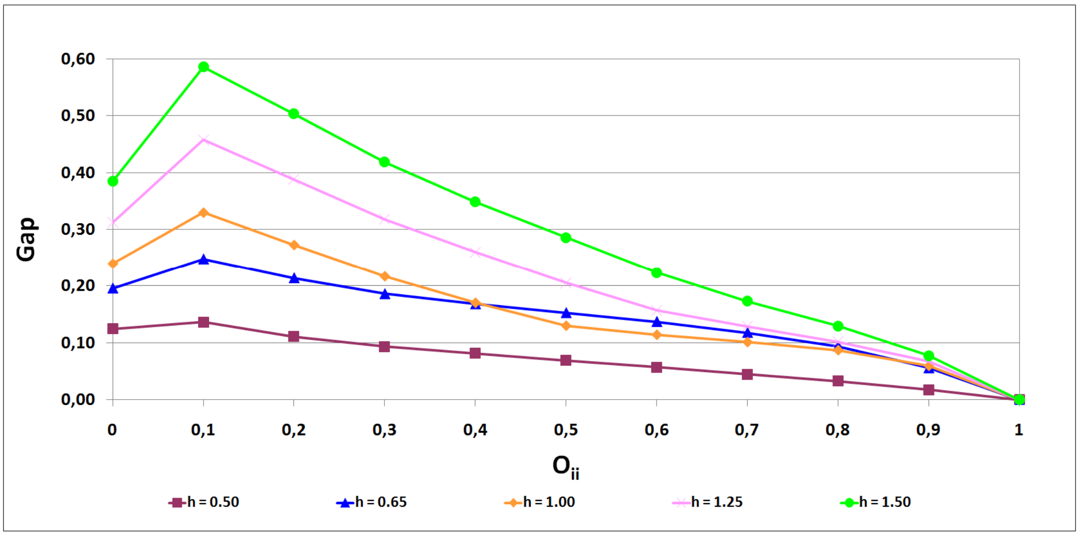

Figure 4.4 - Gap between profits obtained by heuristic and optimal policies under different holding cost values vs. O_{ii} for triple-state observation under R=5, ℓ=2, λ=0.35 and A={p,dp}×{0,1,…,5}

Figure 4.4 shows the gap between profits by heuristic and optimal policies under various holding cost values. Note that, there are two different full information policies adopted by the holding cost values shown in Figure 4.4. The first one is obtained under h=0.50 and h=0.65, the second one is obtained under h=1.00, h=1.25 and h=1.50.

Under high holding cost (h=1.00, h=1.25 and h=1.50), the full information policy keeps no stock. The optimal policy keeps the same base stock level as the full information. For higher O_{ii} values, the optimal policy keeps higher base stock and quotes longer lead times compared to low O_{ii} values. On the other hand, under heuristic policy, for all O_{ii} values the base stock level is higher than full information policy and does not change. Since this policy is pursued under all the high holding cost values under heuristic policy, an increase in the holding cost contributes a fall in the profits. Note that, as shown in Figure 4.4, as holding cost increases, the gap between profits may decrease if the policy under full information changes with the holding cost. For example when O_{ii}=0.5, an increase holding cost from 0.65 to 1.00, narrows the gap between the profits.

Note that, in Figure 4.4, the widest profit gap is obtained under the self–state observation probability where the value of information is highest under heuristic policy. In other words, the O_{ii} value where the lowest profit is earned under heuristic policy determines the O_{ii} value where the widest gap is obtained. Therefore the maximum decrease in the profit under heuristic policy is higher than the maximum decrease in the profit under optimal policies under the same holding cost. Being able to take different actions for changing O_{ii} values makes a slight fall in the profits under optimal policy. However, taking the same actions under heuristic policy causes sharp declines in the profits.

The gap between the optimal and heuristic policies under varying customer arrival rates is shown in Figure 4.5.

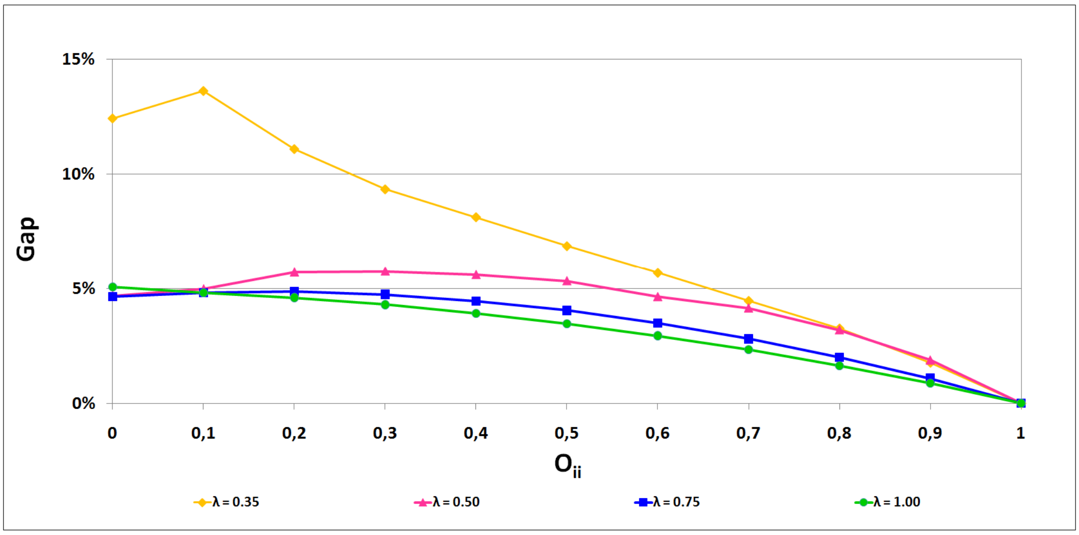

Figure 4.5 – Gap between profits obtained by heuristic and optimal policies under different customer arrival rates vs. O_{ii} under triple state observation under R=5, ℓ=2, h=0.35 and A={p,dp}×{0,1,…,5}

As shown in Figure 4.5, the gap between the profits under heuristic and optimal policies narrows as the customer arrival rate increases. The underlying reason for the narrowing gap between the policies is closely related with having a base stock level higher than full information base stock level. Note that, under heuristic policies, the base stock level is always higher than full information base stock level (the reason for a higher base stock level lies under randomized actions). Under optimal policies, under low customer arrival rates, the full information base stock level is adopted for low and middle O_{ii} values. Therefore, as shown in Figure 4.5, the gap between the policies under $\boldsymbol{\lambda}$=0.35 is substantial for low and middle O_{ii} values. On the contrary, the gap is narrower under high customer arrival rates, since under optimal policies the base stock level is higher than full information base stock level like under heuristic policies. Therefore, the effect of a higher base stock level under heuristic policies is mitigated.

Although lower profits are generated under heuristic policies than under optimal policies, the performance of heuristic policies is outstanding with respect to computational time. In general, the time spent under heuristic policies is almost %95 lower than under optimal policies. The time gap between the two policies can widen up to %99 under certain circumstances especially when O_{ii} takes middle values. The heuristic policy can be preferred to optimal policy under high customer arrival rates as the profit gap is insignificant under these high rates when compared with the ones under other changing parameters. □

4.2 Analysis of Heuristic and Optimal Partial Information Policies in the Presence of Double-State Observation

In this section, heuristic and optimal policies under partial information are compared in the presence of double-state observation under different parameters.

As mentioned, under double–state observation, two states can be observed under two structures, DSOF or DSOL. Under DSOF, when the manufacturer observes state i, the core process can be i or i+1 with probabilities π_{ii} and $\pi_{i+1,i}$, respectively. On the other hand, under DSOL, when the manufacturer observes state i, the core process can be i and i-1 with probabilities π_{ii} and $\pi_{i-1,i}$, respectively.

Under double–state observations under different holding cost values, the profits under optimal policies are given in Figure 4.6.

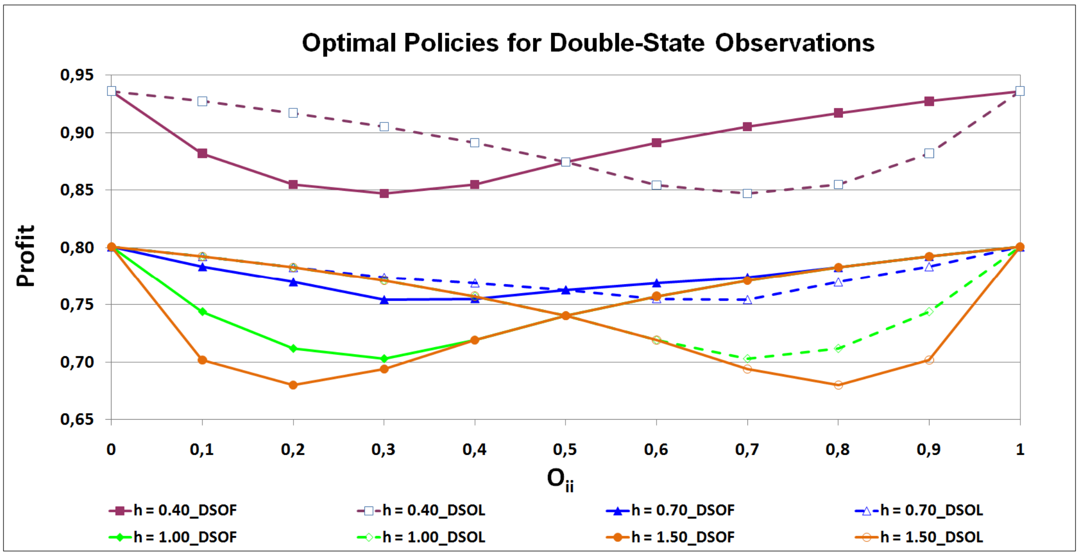

Figure 4.6 - Profits obtained by optimal policies under different holding costs vs. O_{ii} under double state observation under R=5, ℓ=2, λ=0.35 and A={p,dp}×{0,1,…,5}

Note that in Figure 4.6, under O_{ii}=0 and O_{ii}=1, the same profit is generated under both DSOF and DSOL structures under the same holding cost. The reason for the same profit is that the observation matrices under O_{ii}=0 and O_{ii}=1 form the "perfect observability class" (Zhang, 2010). Therefore, the system state is revealed by the action set, i.e. perfect observability applies.

A careful examination of Figure 4.6, also reveals that the profits earned under DSOL and DSOF structures under the same holding cost are highly symmetrical with respect to self-state observation probabilities. For instance, under h=0.40, the profit realized under DSOF structure when O_{ii}=0.20 is nearly equal to the profit made under DSOL structure when O_{ii}=0.80. The reason is that the structure of the policy is substantially same under both DSOL and DSOF. The difference between the policies lies in the states and the probabilities of the randomized actions. The action taken in the observed state i under DSOL structure is roughly same as the action taken in the observed state i-1 under DSOF structure. Note that, there are subtle differences in probabilities of taking a randomized action under symmetrical DSOL and DSOF structures.

Observation 5*: Under DSOF, low O_{ii} leads to higher base stock compared to full information, whereas under DSOL high O_{ii} leads to higher base stock compared to full information.*

Under DSOF, when actual state is i, observed states are i or i -1. In other words, when observed state is i, actual state is i or i +1. When O_{ii} is low, steady-state analysis shows that given observed state is i, π_{ii} .and $\pi_{i+1,i}$ are close to each other. Therefore, the manufacturer has a tendency to quote wrong lead times since the information availability is low. To mitigate the effect of wrong lead time quotation the system increases the base-stock level. For high self-state observation probabilities, steady state analysis shows that π_{ii} is much higher than $\pi_{i+1,i}$. Therefore, the lead time quotes gets closer to full information lead time quotes. Similar behavior is observed under DSOL under high O_{ii} values. In those cases, i, π_{ii} .and $\pi_{i-1,i}$ are close to each other. As under DSOF under low O_{ii} values, to minimize the effect of wrong lead time quotation, a higher base stock level than full information base stock policy is kept. Since extra stock is kept, an increase in holding cost decreases the profits under partial information. However, as opposed to DSOF structure, under low O_{ii} values, $\pi_{i-1,i}$ is much higher than π_{ii}. Since one of probabilities is much higher than the other, the information availability is high for the manufacturer under imperfect information. This explains the symmetric behavior in Figure 4.6.

The behavior of profits generated under *heuristic* policy for both DSOF and DSOL structures is similar to optimal policy. The profits yielded under DSOF and DSOL structure heuristic policy are nearly symmetrical as under optimal policies. However, due to their inflexibilities, the same policy structure is adopted for $0 < O_{ii} < 1$ under the same full information policy.

The behavior of profits under different customer arrival rates for DSOF and DSOL structures are similar with the ones under different holding cost values. □

4.3 The Effect of Make-to-Stock (MTS) vs. Make-to-Order (MTO) Schemes on Value of Information

In this section, MTS and MTO schemes are examined under triple state observation under optimal policies to see the effect of schemes on value of information. To assess the effect, the profit gap under two schemes is analyzed under different parameters for fixed O_{ii} values. In this section, we use the following performance measure;

$$VoI_{MTO} = \frac{\text{Profit}_{MTO}^{full} - \text{Profit}_{MTO}^{opt}}{\text{Profit}_{MTO}^{full}} \quad \textbf{(4.6)}$$

Under both full and partial information, a MTS scheme carries optimal level of inventory whereas under a MTO scheme no inventory is carried, i.e. base stock level is zero. The manufacturer operating under a MTS scheme can take both lead time quotation and production decisions at any observed state. On the other hand, the manufacturer operating under a MTO scheme can only take production and lead time quotation decisions for $i'>0$. Note that, under partial information, under MTO scheme, when the actual state is zero, i.e. $i=0$, a manufacturer can only observe two states $i'=0$ and $i'=1$.

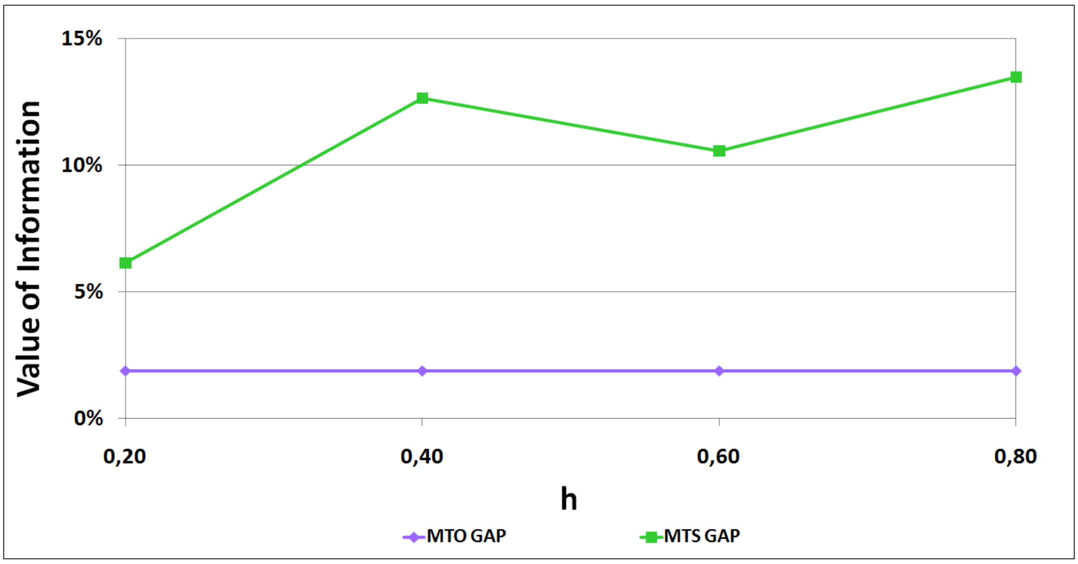

Figure 4.7 – Profit gap between MTS and MTO schemes and full information vs. h under R=5, ℓ=2, λ=0.35, O_{ii}=0.40 and A={p,dp}×{0,1,…,5}

As shown in the figure above, an increase in the holding cost does not affect the profit generated under MTO schemes. The reason is, under an MTO scheme the manufacturer does not keep any stock. Hence, an increase in the holding cost does not have any effect on the profit. On the other hand, an increase in the holding cost affects the profit under an MTS scheme. Under relatively low holding cost, the gap between partial information and full information MTS scheme is narrow. Under relatively low holding cost (h=0.20), the base stock level is higher under partial information MTS scheme than full information MTS scheme. However, the effect of a higher base stock level is modest since the holding cost is low. On the other hand, high holding cost has significant effect when the partial information base stock level is higher than full information base stock level. Under relatively high holding cost (h=0.80), the manufacturer does not keep any stock under full information MTS scheme, i.e. the manufacturer operates under a MTO scheme. But, under partial information MTS scheme, the manufacturer has a base stock level greater than zero. Therefore, a higher base stock level than full information has a powerful effect on the profit generated under partial information when the holding cost is high.

When the value of information is analyzed under full information with respect to increasing arrival rates, it is observed that under relatively low customer arrival rates, the base stock level is zero. Therefore, the manufacturer under full information operates under a MTO scheme. On the other hand, under high customer arrival rates, under full information, the manufacturer operates under a MTS scheme.

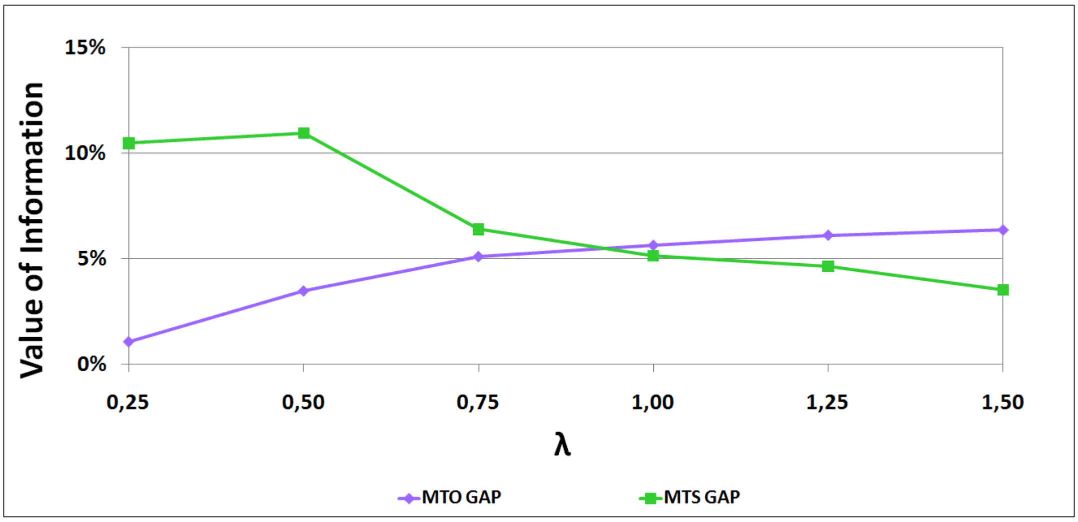

Figure 4.8 – Profit gap between MTS and MTO schemes and full information vs. h under R=5, ℓ=2, h=0.50, O_{ii}=0.40 and A={p,dp}×{0,1,…,5}

As shown in the figure above, an increase in the customer arrival rate causes the value of information under MTO scheme to increase. There are two effects behind the increase in the value of information under partial information MTO scheme. The first effect is as follows. Given that observed state is i; it is more likely that actual state is i-1, i, i +1 for i'>0. Hence lead time quotes are ineffective for i'>0. On the other hand, when i'=0, most of the time lead time quote is 0. Thus under i'=0, lead time quote is effective. The second effect is as follows. As the customer arrival rate increases, system spends more time under ineffective lead time quote region, i.e. i'>0. Thus this leads to decrease in profit. Therefore, value of information is higher under high customer arrival rates.

The decline in the value of information under MTS scheme with increasing customer arrival rate is related with having a high base stock level. As mentioned in Section 4.1, under partial information, the policy may prefer to quote positive lead times when there are items in the stock, and the effect of positive lead time quotation is much more noticeable when the base stock level is one, while the effect vanishes as base stock level increases. Under high customer arrival rates, under MTS scheme, base stock levels are high. Therefore the effect of positive lead time quotation is mitigated and the value of information decreases with increasing customer arrival rate. □

4.4 The Effect of Lead Time Quotation Policies on the Value of Information

In this section, different lead time quotation policies are examined to find the effect lead time quotation policies on information distortion. Firstly, we consider a manufacturer who accepts all the customers, i.e. maximum due date is not quoted to any customer. Secondly, a manufacturer where the customers are either accepted or rejected is considered. Thirdly, as in Section 4.1, a manufacturer who quotes precise lead times to customers will be examined. The aim is to find under which lead time quotation policy the benefit of information is highest.

All of the analysis is made under optimal policies for triple–state observation. The analysis will be conducted on increasing holding cost values firstly, and then on increasing customer arrival rates. To assess the performance of policies, the gap between the profits under partial information and corresponding full information will be employed. In this section, we use the following performance measure to assess the value of information;

$$VoI_{MTO} = \frac{\text{Profit}_{LTQP}^{full} - \text{Profit}_{LTQP}^{opt}}{\text{Profit}_{LTQP}^{full}} \qquad \textbf{(4.7)}$$

where $\text{Profit}_{LTQP}^{full}$ and $\text{Profit}_{LTQP}^{opt}$ denote the profit for a lead time quotation policy obtained under full information and partial information optimal policy respectively.

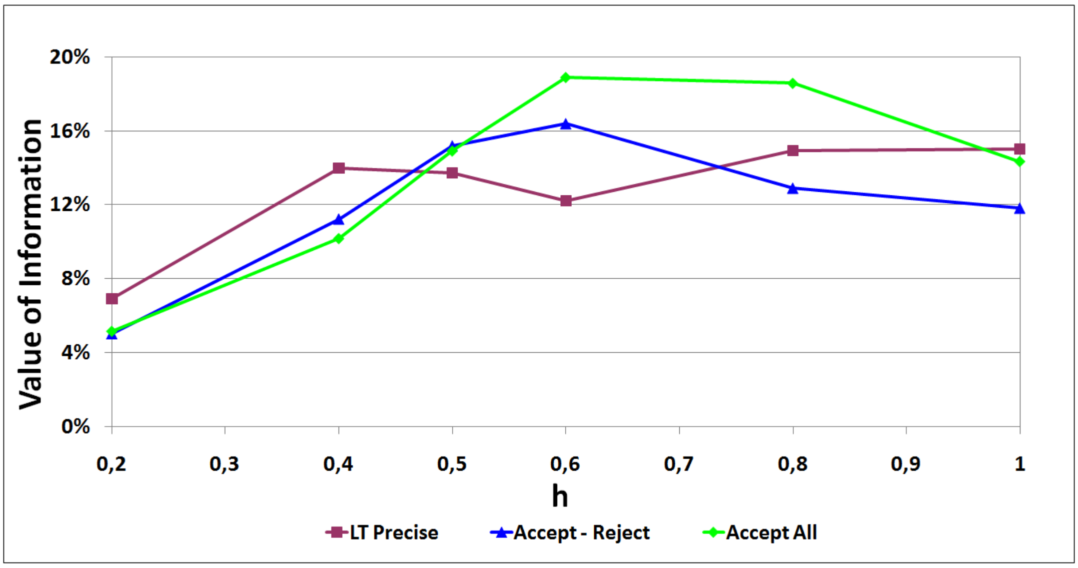

Figure 4.9 - Profit gap between partial information and full information lead time policies vs. h under R=5, ℓ=2, λ=0.35

Under increasing holding cost, it is hard to decide on under which lead time quotation policy the benefit of information is highest. The base stock levels obtained under partial information accept-all policies are higher than under partial information accept-reject and precise lead time policies. Therefore, the changes in holding cost are remarkably effective on partial information accept-all policies. The positive lead time quotation when there are items in the inventory may take place under partial information precise lead time quotation policy. However, positive lead time quotation policy does not take place under partial information accept-reject policy, since this would mean to reject the customer when there are items in the inventory (the manufacturer can only quote 0 or maximum lead time). Therefore, the positive lead time quotation policy is not effective under partial information accept-reject policies.

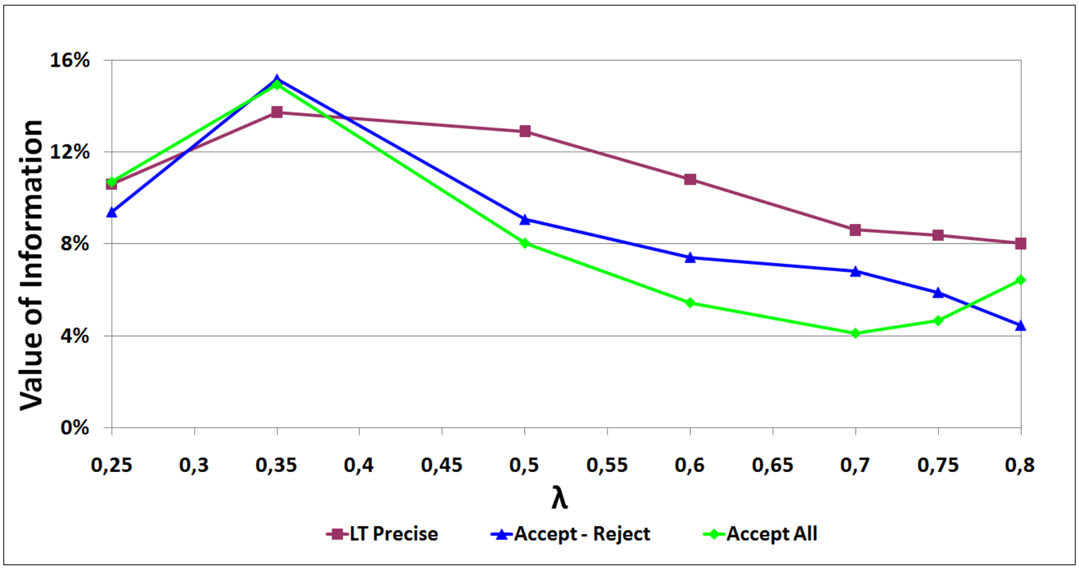

Figure 4.10 - Profit Gap between Partial Information and Full Information Lead Time Policies vs. h under R=5, ℓ=2, h=0.50

As shown in the figure above, the value of information is generally highest under partial information precise lead time quotation policies, and generally lowest under partial information accept-all policies. The reason behind is the base stock levels adopted. As mentioned above, the highest base stock levels are obtained under accept-all policies. Under relatively low customer arrival rates, the highest holding cost is incurred under partial information accept-all policy. However, with increasing customer arrival rates, the base stock levels under partial information lead time policies get closer. Therefore, the effect of a higher base stock level is mitigated. Under relatively high customer arrival rates, however, partial information accept-all policy has the highest base stock level. Therefore, the value of information increases under partial information accept-all policy as opposed to other partial information lead time policies.

Note that, wrong lead time quotation is not possible under both accept-all and accept-reject policies. This implies higher information availability under precise lead time quotation schemes.□

CHAPTER 5

CONCLUSION

In this study, we consider a manufacturer taking production and lead time quotation decisions in an environment where the exact status of production is not directly observable but rather partially observable. The manufacturer's aim is to find the joint optimal production and lead quotation policy that maximizes her profit. We try to assess the value of information by comparing the profit generated and the policy followed by a manufacturer who does not face any information distortion, i.e. can access to perfect information, with another manufacturer in the presence of information distortion. A stochastic model is introduced to find the optimal joint production and lead time quotation policy under perfect information. To find the optimal decisions for the manufacturer facing information distortion, Partially Observable Markov Decision Process is employed. We study two approaches for the manufacturer facing information distortion. In the first approach, we introduce a nonlinear programming model to find the optimal decisions. In the second approach, a heuristic approach, constructed on optimal actions taken under perfect information is represented. To examine the value of information, we define information distortion with two specific structures, triple-state, where the manufacturer can observe states i-1, i, i+1, and double-state observations i-1, i or i+1, i when the actual state is i. Under both structures, we allow the manufacturer to observe the state i when the actual state is i with a probability named *self-state observation probability*. We analyze the value of information under different parameters by adopting the policies under nonlinear programming model and heuristic approach under triple-state observations. Interesting observations are made during analyzes.

Firstly, it is found that, an increase in self-state observation probability does not necessarily lead to an increase in the profit. Secondly, it is demonstrated that as the holding cost increases the value of information also increases even if the operating scheme is MTO under full information. Moreover, under increasing customer arrival rates, the self-state observation probability giving the highest value of information is shown to be decreasing. We then compare the optimal policies and heuristic policies under information distortion. We observe that, optimal policy is more robust to the changes in self–state observation probability than the heuristic policy under partial information. In addition, it is observed that as holding cost increases, the profit gap between the heuristic and optimal policies increases under the same self–state observation probability given that the system operates under the same policy under full information. We also analyze the value of information under double-state observation by introducing two structures, DSOL and DSOF. The profits under DSOL and DSOF are seen to be highly symmetrical. Analysis show that; under DSOF, higher base stock levels compared to full information are obtained under low self-state observation probabilities, whereas under DSOL higher base stock compared to full information are attained under high self-state observation probabilities. Then, the effect of MTS and MTO schemes is investigated under triple state observation under optimal policies to see the effect of schemes on value of information. The value of information is found to be higher under partial information MTS scheme than MTO scheme under increasing holding cost. However, the value of information is lower under partial information MTS scheme than partial information MTO scheme under high customer arrival rates. Finally, the effect of different lead time quotation policies; accept-all, accept-reject and precise lead time quotation, on value of information is studied. Under low customer arrival rate, the effect of holding cost on value of information cannot be compared under different schemes. However, under high customer arrival rates, the value of information under precise lead time quotation policy is generally found to be higher than the other quotation policies.

The analysis made in this study can be extended in many future research directions. Firstly, in this study, the fixed cost of production is assumed to be zero. The fixed cost of production can be assumed to be greater than zero and a different policy structure is obtained. Secondly, we confine the information distortion into two specific structures. Other information distortion structures, especially the ones where the asymmetric observation probabilities take place, may be defined and examined. Thirdly, we considered a single acceptance probability function. Other probability functions can be defined, and the effect of acceptance probability on the policies may be analyzed. Lastly, the revenue earned from any customer who has placed an order is assumed to be the same. The revenue earned from a customer who has placed an order is assumed not to be the same and two different customer classes can be considered in the problem.

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