PERFORMANCE ANALYSIS OF A HYBRID SYSTEM UNDER QUALITY IMPACT OF RETURNS

by

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ABSTRACT

PERFORMANCE ANALYSIS OF A HYBRID SYSTEM UNDER QUALITY IMPACT OF RETURNS

Remanufacturing is the process which transforms used products, consisting of components and parts, into products that satisfy the same quality and other standards as new ones. Systems that remanufacture used products face several complicating factors that limit the effectiveness of traditional methods for manufacturing planning and control. Original equipment manufacturers that choose to remanufacture their own products can either meet the demand with remanufactured products, or new products, or a combination of both when they are perfect substitutes. Such systems are referred to as hybrid production systems.

In this study we analyze a hybrid system which meet the demand with remanufactured products, or new products, or a combination of both. In the remanufacturing stage there are uncertainties in the quality of remanufactured products, return rates and return times of these returned products. These uncertainties affect the raw material order quantities, processing times and material recovery rates. In the study returned products are classified by considering quality uncertainties and remanufacturing processing times, material recovery rates, remanufacturing costs and disposal costs are determined according to this classification. The objective of the study is to examine the inventory control model that balances the system throughput with the order arrivals and minimizes the total cost per unit. In order to compare several inventory control strategies simulation models are constructed by using the ARENA simulation program. In the conclusion of the study it is denoted that classifying returned products according to quality uncertainties decreases the total cost per unit and the best inventory control model for the analyzed hybrid system is proposed.

ÖZET

KULLANILMIŞ ÜRÜNLERİN KALİTE BELİRSİZLİKLERİ ALTINDA BİR MELEZ SİSTEMİN PERFORMANS ANALİZİ

Yeniden üretim, kullanılmış ürünlerin, kalite ve diğer standartlara uygun şekilde yeni ürünlere dönüştürülmesi sürecidir. Kullanılmış ürünleri yeniden üretim sürecinde değerlendiren sistemler, geleneksel üretim planlama ve kontrol yöntemlerinin verimliliğini azaltan çeşitli faktörlerle yüzyüze kalmaktadır. Yeniden üretim sistemlerinde üreticiler talepleri, yeniden değerlendirilen ürünlerle, yeni ürünlerle veya bunların karışımı ile karşılayabilirler. Bu tip sistemlere melez üretim sistemleri denilmektedir.

Bu çalışmada; talebi yeni veya yeniden üretilmiş üründen karşılayan bir melez üretim sistemi incelenmiştr. Yeniden üretim hattında, girdileri oluşturacak olan kullanılmış ürünlerin kalitesinde, geri dönüş miktarında ve geri dönüş zamanında belirsizlikler vardır. Bu belirsizlikler hammadde sipariş miktarını, işlem sürelerini ve malzeme kullanım oranlarını etkilemektedir. Bu çalışmada kullanılmış ürünlerin kalite belirsizlikleri göz önüne alınarak bu ürünler üzerinde bir sınıflandırma yapılmış ve bu sınıflandırmaya göre yeniden üretim işlem süreleri, malzeme kullanım oranları, yeniden üretim maliyetleri ve atık maliyetleri belirlenmiştir. Çalışmanın amacı sistem çıktısını istenilen sipariş miktarları ile en iyi dengeleyecek ve ürün başına düşen maliyeti en küçükleyecek stok kontrol modelini araştırmaktır. Çeşitli stok kontrol stratejilerini karşılaştırmak amacıyla ARENA simülasyon programı kullanılarak simülasyon modelleri kurulmuştur. Çalışmanın sonucunda kullanılmış ürünlerin kalite belirsizlikleri göz önüne alınarak sınıflandırılmasının ürün başına düşen toplam maliyette düşüş sağladığı belirlenmiş ve melez sistemler için en uygun stok kontrol modeli sunulmuştur.

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B	Backorder capacity
c	Standard deviation multiplier
C_b	Backorder cost per unit
C_{class}	Classification cost per unit
C_{ls}	Lost sales cost per unit
C_R	Returned product purchasing cost per unit
C_{RW}	Raw material purchasing cost per unit
CD_{fps_r}	End stock disposal cost per unit for remanufactured products
CD_{fps_m}	End stock disposal cost per unit for manufactured products
CD_j	Overflow disposal cost per unit for overflows from buffer j
CDO_i	Operational disposal cost per unit for return product of quality i where $i = 1, 2, 3$
CDO_r	Operational disposal cost per unit
CH_{fps}	Finished parts holding cost per unit/time
CH_j	Holding cost per unit/time for the number in the j^{th} queue
CP_a	Assembly cost per time
CP_m	Manufacturing cost per time
CP_r	Remanufacturing cost per time
CP_{r_i}	Remanufacturing cost per time for return product of quality i where $i = 1, 2, 3$
f	Proportion of expected processing time of the manufacturing operation over the expected processing time for the remanufacturing process
h	Out-of-pocket holding cost rate
i	Quality of returns where good(1), average(2), bad(3)
K	FPS capacity/blocking limit
k_i	Probability for return arrival of quality i where $i = 1, 2, 3$
K_j	Buffer capacity/blocking limit for buffer j
n_1	Currently present number in the FPS

n_2	Currently present number of backorders
ν_a	Average rate of of assembled products
N_b	Expected number of backorders
N_{ls}	Average rate of of lost sales
ν_m	Average rate of of manufactured products
ν_r	Average rate of of remanufactured products
ν_{r_i}	Average rate of of remanufactured products for return product of quality i where $i = 1, 2, 3$
ND_{fps}	Average rate of of end stock disposals
ND_j	Average rate of of overflow disposals from buffer j
NDO_i	Average rate of of operational disposals from remanufacturing process for return product of quality i where $i = 1, 2, 3$
NDO_r	Average rate of of operational disposals from remanufacturing process
NQ_{fps}	Expected number in the FPS
NQ_j	Expected number in the j^{th} queue
$P00$	Steady state probabilities for synchronization station
$P[0]$	Steady state probabilities for synchronization station
$P[n_1]$	Steady state probabilities for synchronization station
r	Proportion of return rate
R	Expected returned products arrival rate
r_{max}	Maximum return rate
RW	Expected raw material arrival rate
TC	Total expected cost per unit
$TC_{noclass}$	Total expected cost per unit with no classification
$TC_{withclass}$	Total expected cost per unit with classification
z_i	Recovery rate for remanufactured product of quality i where $i = 1, 2, 3$
z_r	Recovery rate for remanufactured products
α	Opportunity cost of capital
γ	Demand rate

λ	Arrival rate of the system
λ_{fps}	Throughput of the system
ω	Proportional difference of remanufacturing processing times
π_r	Expected remanufacturing processing time
π_a	Expected assembly processing time
π_m	Expected manufacturing processing time
π_{r_i}	Expected remanufacturing processing time for return product of quality i where $i = 1, 2, 3$
ρ_{avg}	Average utilization

B	Backorder Queue
BAS	Block After Service
CTMC	Continuous Time Markov Chain
EOQ	Economic Order Quantity
FPS	Finished Parts Storage
NOBAP	Near Optimal Buffer Allocation Plan
OEM	Original Equipment Manufacturer
S	Sales

1. INTRODUCTION

In recent years, by the development of production, transportation and communication technologies, consumer goods became more affordable and approachable. This development causes increasing consumption rates which brings depletion of natural resources and increasing raw material costs together. By the developing technology, especially in the electronic products, the useful life of products are shortened. This changing structure of the product life cycles exponentially increases the amount of waste disposals. Besides the effects of developing technologies, rapid changes in the natural environment have also changed the way most companies perform their business. Because of the global problems such as global warming and increasing wastes, producers and consumers become more environmentally conscious. Many producers are trying to find efficient ways of conducting their businesses by minimizing the environmental impact their operations generate. Waste prevention is an efficient way for this purpose. There are several methods of waste prevention and one of them is product recovery. The aim of the product recovery system is to recover as much of the value-added products as possible by reducing waste disposals.

A product recovery system includes processes such as disassembly, repairing, refurbishing, remanufacturing, cannibalizing and recycling of products following the end-of-life of a product [1]. Remanufacturing is "...an industrial process in which worn-out products are restored to like new conditions" [2]. During the remanufacturing operation, firstly a discarded product is disassembled, then parts are cleaned, refurbished, remanufactured and put into inventory, and lastly the new product is reassembled from the old and, where necessary, new parts. Remanufacturing provides many advantages to the producers such as, reducing the amount of wastes and minimizing the consumption of natural resources besides benefits like savings in energy, raw materials, capital and production lead time.

Currently many producers specialize in remanufacturing products. These companies conduct their operations in the same way as traditional manufacturing companies.

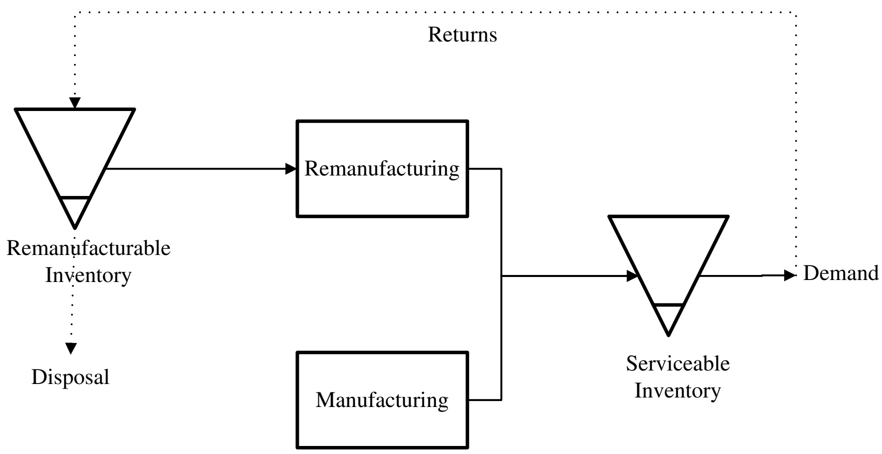

Figure 1.1. A hybrid system with manufacturing and remanufacturing operations

However, some original equipment manufacturers (OEM) may choose to combine manufacturing and remanufacturing activities together. Systems which include both manufacturing and remanufacturing activities are called *hybrid production systems.* This thesis analyses an original equipment manufacturer operating a hybrid system, which includes both remanufacturing and manufacturing operations shown in Figure 1.1. Unlike the traditional production systems,in hybrid production systems the demand can be satisfied by remanufactured products or new products.

Existing production control mechanisms constructed for traditional production systems are inadequate for hybrid systems. Hybrid production systems consist of at least two different parallel production streams which produce to supply the same demand. The remanufacturing stream of this system has different production characteristics which requires new planning and inventory control methods. Remanufacturing companies face several complicating factors such as uncertainties in the quality, quantity and timing of product return flows. These uncertainties in return flows lead to stochastic routings and production lead times. Quality of returns result in uncertainties in the remanufacturing processing times and the recovery rate of the process. Because of these uncertainties it is hard to balance demands with returns. Manufacturers are trying to reduce the variability in the volume and timing of return flows by different applications such as buy-back campaigns or lease contracts. However, quality uncertainties in returns cannot be manipulated as easily.

Typically remanufacturing operations have shorter processing times and consume less energy and natural resources. However, product return rate is always less than or equal to the demand rate which leads companies to manufacture new products besides remanufactured ones in order to satisfy the total demand.

In this study, we model and analyze a hybrid system including both remanufacturing and manufacturing operations allowing different quality levels for return flows. The aim of the study is to test alternative policies that consider the effect of return qualities and to find the most effective policy for the analyzed hybrid system to balance both manufacturing and remanufacturing throughputs with demand. In order to achieve our objective and analyze the system a simulation model is constructed. According to the quality levels of returned products remanufacturing processing times and material recovery rates are determined and performance analysis of the system is made under different parameters and policies. We deal with different inventory control policies and blocking mechanisms. Related cost values are assigned to the system parameters and a cost function is constructed. Optimum values of the cost function are found for different parameters.

The rest of the thesis is organized as follows. The literature survey on hybrid production systems and remanufacturing subject is given in Chapter 2. In Chapter 3 the analyzed problem is defined and research objective is introduced. In Chapter 4 a single stage inventory control model is analyzed. We propose two different multi stage inventory control models in Chapter 5. In Chapter 6, sensitivity analysis on the cost function is analyzed and finally in Chapter 7 the study is concluded by discussing the results of the simulation study of the analyzed hybrid system.

2. LITERATURE SURVEY

Hybrid production systems consist of at least two different parallel production streams which produce to supply the same demand viz. manufacturing and remanufacturing. At the manufacturing stage of this system new products are produced from raw materials while at remanufacturing stage returned items are recovered. Thierry et al. [1] defined the processes of a product recovery system such as repairing, refurbishing, remanufacturing, cannibalizing and recycling of products following the end-of-life of a product. In this thesis we mainly focus on the remanufacturing part of product recovery system.

Remanufacturing is defined by Lund [2] as an industrial process in which worn-out products are restored to like new conditions. Guide [3] made a study to identify and discuss the complicating characteristics of a remanufacturing process that require significant changes in production planning and control activities. According to Guide, the seven characteristics of the remanufacturing process are;

1. The uncertain timing and quantity of returns,
2. The need to balance returns with demands,
3. The disassembly of returned products,
4. The uncertainty in materials recovered from returned items,
5. The requirement for a reverse logistic network,
6. The complication of material matching restrictions,
7. The the problems of stochastic routings for materials for remanufacturing operations and highly variable processing times.

Due to these unique characteristics, the remanufacturing process faces several challenges.

One branch of product recovery research concentrates on production planning and scheduling issues. A state of the art survey on this subject is presented by Guide et al. [4]. They present an overview of the production planning and control problem for remanufacturers. Guide and Srivastava [5] evaluated various order release strategies in a remanufacturing environment using a simulation model for aircraft engine components work shops. Guide et al. [6] examined disassembly release mechanisms and priority dispatching rules via a simulation model. Their results indicate that simple due-date based priority dispatching procedures generally perform well for a variety of performance measures and disassembly release mechanisms had very little impact on performance measures.

2.1. Inventory Control Models

Inventory planning and control is another extended subject examined by product recovery researchers. Inventory management in hybrid systems has received interest in the academic literature relatively recently. Most of the inventory control models for remanufacturing environment assume that the correlation between the demand and the return arrivals is negligible. Remanufacturing systems face the uncertainties in time, quantity and quality of the returned product arrivals. In addition, they need to deal with the uncertainty in materials recovered from returned items. Material recovery rates can be used while establishing an inventory control model with random demand arrivals and lead-time to reflect these uncertainties in the model. Coordinating raw material and used product arrivals in order to supply the demand is another important aspect of hybrid systems. Established model also needs to minimize the total amount of backorders, finished goods inventory and lost sales. All these modeling issues make hybrid system inventory modeling different from traditional inventory control models.

Inventory control models can be analyzed in two classes as uncapacitated and capacitated control models. Uncapacitated control models consider deterministic or probabilistic replenishment lead times for arrival of orders. These models assume that the inventories are replenished within lead times independent of the order size and they do not impose a finite production speed for the end product replenishment process. Capacitated control models consider inventories as queues of jobs before each process while they assign a finite production rate for each process and analyze the balance between minimum inventory levels and maximum output of the system.

2.1.1. Uncapacitated Control Models

Uncapacitated control models can be examined in two classes as deterministic or stochastic models. In deterministic inventory control models the arrival rates of demand and returns are known with certainty. The objective of these models is to find the EOQ (Economic Order Quantity) that balances the set-up costs with inventory holding costs. Mabini et al. [7] developed EOQ formula for hybrid system with deterministic demand and lead times. Richter [8]; Richter and Dobos [9]; Richter and Sombrutzki [10] are examples for the deterministic models where they aimed to examine the effect of returns on the optimal order quantity. Teunter [11] studied a deterministic system where a disposal option is included.

The first stochastic model was proposed by Simpson [12]. It assumes stochastic and mutually dependent demands and returns. Remanufacturable products can be disposed if they are not needed. Outside procurement satisfies the demand that is not fulfilled by used product returns. The system is controlled by a PULL strategy. However as a limitation of this model, remanufacturing and outside procurement lead times are assumed to be zero, and fixed manufacturing and outside procurement costs are not taken into account. Kelle and Silver [13] constructed a model where they assume that demand and return processes are totally independent and no disposal occurs. The system is controlled by a PUSH control strategy. Additionally, the cost function include fixed outside procurement costs , and service is modeled in terms of a service-level constraint instead of backordering costs. Teunter and Vlachos [14] analyzed the impact of the disposal option by using discounted average cost method. According to their study, when there are more demands than returns and remanufacturing is marginally profitable, it is in general not necessary to include a disposal option for returned products. Mahadevan et al. [15] studied a remanufacturing facility with returned products and demands following a Poisson process. Their objective was to answer the questions such as when to release returned products to the remanufacturing line and how many new products to manufacture. They did not consider returned product disposals in their model.

On the other hand the first continuous review model was studied by Heyman [16] . He studied a situation with stochastic uncorrelated demands and returns where the objective was to determine the optimum inventory level that minimizes the total inventory holding costs. He used a PUSH strategy with disposal options. As in discrete time models, a limitation of this model is that remanufacturing and outside procurement lead times are zero. Muckstadt and Isaac [17] considered lead times but ignored disposal option. Extensions of the Muckstadt and Isaac model to include the disposal of returned products was studied by van der Laan, Dekker and Salomon [18]. They showed that disposal is a necessary option for cost minimization. Van der Laan and Salomon [19] studied a stochastic hybrid inventory system with disposal operations. They have extended the the PUSH and PULL strategies to coordinate production, remanufacturing and disposal operations. They concluded that disposal can be effective only if it reduces the variability in the systems' inventories. PULL disposal strategy is favorable over PUSH disposal strategy only if remanufacturable inventory is valued lower than serviceable inventory, otherwise PUSH disposal strategy is more favorable. Van der Laan et al. [20] compared traditional systems without remanufacturing to PUSH and to PULL controlled systems with remanufacturing.

2.1.2. Capacitated Control Models

Capacitated control models are the more complex problems of inventory control models. They are generally based on queuing networks with stochastic return, demand and service rates. Korugan and Gupta [21] constructed a two echelon inventory system with stochastic lead times and arrival rates. They used a PUSH type make to stock open queuing network. They concluded that as the return rates increase, expected total cost decreases when the holding cost of returned products at the lower echelon is lower than the lost sales costs. Souza and Ketzenberg [22] modeled a hybrid system considering service level constraints. They used a two stage $GI/G/1$ queuing network model to analyze the system. They assumed both remanufactured and new products are perfect substitutes for satisfying make to order demand and they included the disposal option in their model. Their objective was to find the optimal product mix to satisfy the total demand. Souza et al. [23] analyzed a remanufacturing facility using a $GI/G/1$ queuing network. They aimed to find the optimal product mix over the long run that maximizes profits while maintaining a desired service level. They modeled the remanufacturing facility as a multi class open queuing network where classes are determined according to quality levels of returned products. They considered different remanufacturing stations special for different quality type returns. Different quality types can be processed at each machine bu at a higher time if this machine is not special for that type. They applied dispatching rules to remanufacturing stations and analyzed their effects. They concluded that the choice of the dispatching rule is important in reducing flow times and improving service levels. Guide et al. [24] proposed a remanufacturing model which handles two remanufacturable products. In their model both remanufacturing facilities have limited capacity and are modeled as $M/G/1$ queues. They objective is to minimize total weighted average sojourn time by implementing non-preemptive static priority rules. Bayindir et al. [25] presented a hybrid production system in order to evaluate the inventory related costs. They chose return ratio as the decision variable and used an order up to policy. When demand occurs, depending on the return ratio previously sold items are returned to the system after the end of their useful lifetimes while new parts are ordered and received following a stochastic lead time. Then returned products are remanufactured and are sent to the assembly operation where they are mixed with new products. The authors modeled the system as an open queuing network with $M/G/\infty$ queues. They concluded that when the capacity restriction of the remanufacturing and manufacturing operations is negligible, remanufacturing option does not provide any cost benefits. On the other hand, when capacity constraints are taken into account, remanufacturing becomes profitable. Aras et al. [26] constructed a continuous time Markov chain model in order to analyze the effect of returned products quality on the remanufacturing and disposal decisions. They used a PULL disposal strategy. They included quality based remanufacturing lead times and disposal costs. They concluded that quality based categorization is most effective when quality difference between returned products is high, the quality of both return types is low, return rate is high and demand rate is low. Aksoy and Gupta [27] examined a near optimal buffer allocation plan (NOBAP) developed for a remanufacturing cell with finite buffers and unreliable servers. They proposed an algorithm that uses an open queuing network, decomposition principle and expansion methodology to analyze the remanufacturing cell. The algorithm distributes a given number of available buffer slots among the various stations to optimize the system performance.

In our previous studies we analyzed the impact of the quality uncertainties of returned products by different models. In the first study [28] we analyzed a hybrid system under general distributed processing times with different variances and in the second study [29] we used an average utilization rate for the system and analyzed different priority strategies on the returned products.

3. PROBLEM DEFINITION AND RESEARCH OBJECTIVES

3.1. Problem Definition

We model and analyze a hybrid system with remanufacturing operations differentiating quality levels for return flows. We can satisfy the demand by either remanufactured or new products. The model is depicted in Figure 3.1. At the manufacturing stage new products are manufactured from raw materials and sent to the assembly stage. At the remanufacturing stage, returned products are first inspected and classified according to their quality status. We classify returned products into three quality levels as good quality returns, average quality returns and bad quality returns where they require minimal, average and major remanufacturing effort, respectively. After classification, returned products go to the remanufacturing station which includes disassembly of returned products and recovery of parts. The yield at the remanufacturing process is not perfect as some of these returns cannot be remanufactured due to some unforeseen defects that are detected after disassembly. After manufacturing and remanufacturing processes the new and the 'as good as new' products are sent to assembly station.

We assume that the demand follows an independent Poisson process with parameter γ. We assume that the arrival rate of system (λ) is also Poisson and greater than the demand rate. The returned product arrival rate is determined as the proportion of demand rate ($r\gamma$). The returned product arrival rate must always be smaller than or equal to the demand rate since at most all the satisfied demand can return to the system.

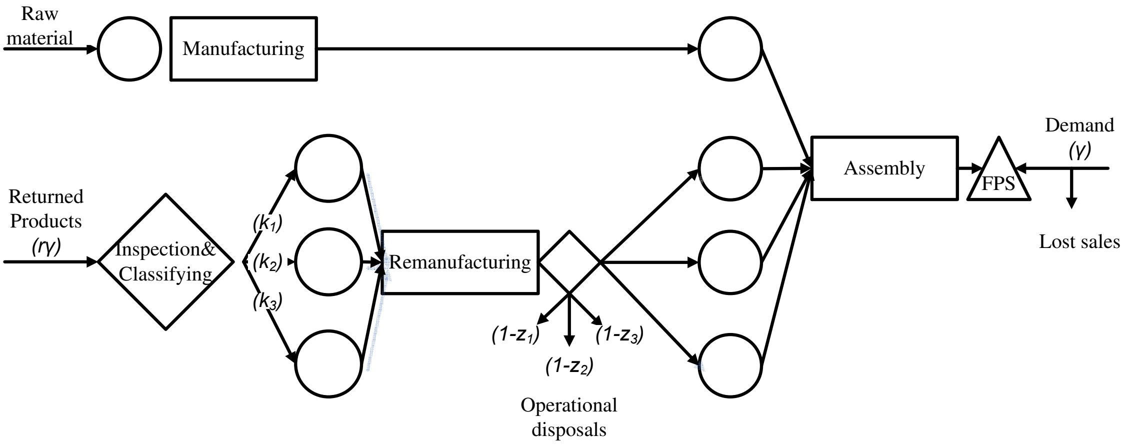

Figure 3.1. Analyzed model

$$\begin{aligned} &\lambda \geq \gamma \\ &r\gamma \leq \gamma \quad ; (0 < r < 1) \end{aligned} \tag{3.1}$$

Return flows are classified into three groups with respective probabilities k_i where i $(i = 1, 2, 3)$ represents the quality of returns $i = 1$ means good quality, $i = 2$ means average quality and $i = 3$ means bad quality respectively. Since we assume the yield at the remanufacturing operation is not perfect, material recovery rates for the remanufacturing operation are determined depending on the quality class of returns (z_i).

The average throughput rate of the manufacturing stage accounts for the difference between the total arrival rate and the expected throughput of the remanufacturing process. Following the assembly operation products are sent to the finished parts storage (FPS) in order to meet the demand, where unsatisfied demand is backordered.

Typically remanufacturing operations have shorter processing times and consume less energy and natural resources. We reflect this situation in the model. On the other hand, remanufacturing processing times change in relation with the quality levels of returns.

In this study at the first stage the analytical model of the system is proposed for the single stage inventory control case. Later general distributions are used for the remanufacturing stage and these cases are analyzed using a simulation model.

3.2. Objectives

The aim of the study is to find the most effective policy for the analyzed hybrid system to balance both manufacturing and remanufacturing throughputs with demand. Because of the stochastic nature of the system, it is almost impossible to balance the system with zero backorders or lost sales. Therefore we balance the finished goods inventory by using different inventory control mechanisms. On the other hand, different from the previous remanufacturing literature we classify returned products into three quality levels in order to analyze the impact of quality uncertainty of returns. This classification enables us to determine different processing times and material recovery rates for different quality levels of returns which reflects a more realistic remanufacturing environment. Afterwards, related cost values will be assigned to the system parameters and a cost function will be constructed. Optimal values of the cost function will be searched for the control variables of different control policies and parameters.

4. SINGLE STAGE INVENTORY CONTROL

4.1. Model-1

This model assumes that all buffers in the hybrid system have infinite capacities and is modeled as a network of a single class $M/M/1/\infty$ queues, only the finished products storage (FPS) has a finite capacity (K) and is modeled as a single class $M/M/1/K$ queue (Figure 4.1). Therefore in this model we can only control FPS capacity in order to minimize the objective function. Here objective function is the total expected cost per unit (TC) where related parameters and values are explained below.

In the model we can satisfy the demand by either remanufactured or new products. At the manufacturing stage new products are manufactured from raw materials and sent to the assembly stage. At the remanufacturing stage, returned products are inspected and classified according to their quality status. We classify returned products into three quality levels as good quality returns, average quality returns and bad quality returns where they require minimal, average and major remanufacturing effort respectively. After classification returned products go to the remanufacturing station which includes disassembly of returned products and recovery of parts. The yield at the remanufacturing process is not perfect as some of these returns cannot be remanufactured due to some unforeseen defects that are detected after disassembly. After manufacturing and remanufacturing processes the new and the ‘as good as new’ products are sent to the assembly station. In the model we have totally eight buffers and finished products storage. The first buffer stands for the raw material arrivals before the manufacturing operation. We have three buffers before the remanufacturing operation for different quality returned products. Returned products with different quality status are remanufactured at the same station but we assign different buffers to different quality returned products in order to assign different holding costs to these products. Before the assembly station all the products are assumed as ‘as good a new’ products but at this stage we also separated the buffers of incoming arrivals from manufacturing station and remanufacturing station. The incoming arrivals from remanufacturing station to the assembly station are placed in different buffers as these products have different holding costs.

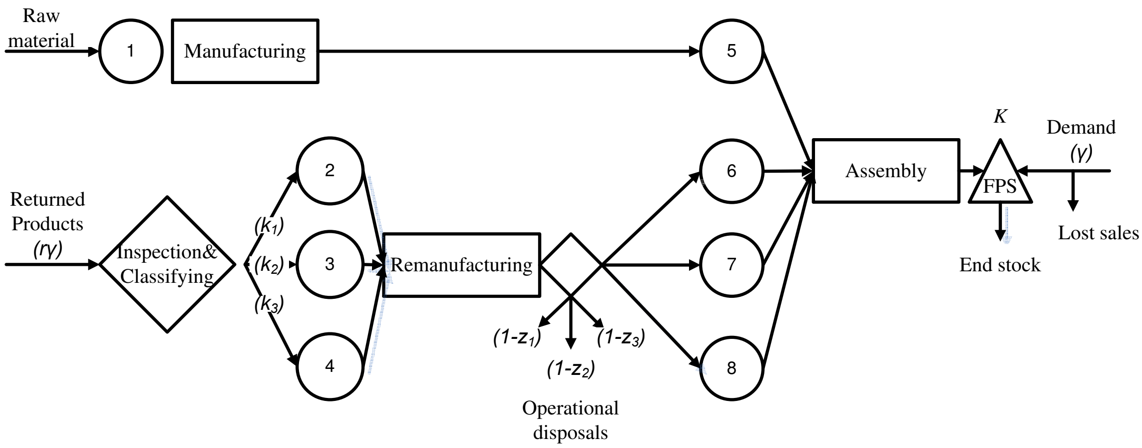

Figure 4.1. Model-1

System Parameters:

γ	demand rate
λ	arrival rate of the system
r	proportion of return rate
k_i	probability for the returned product being quality i where $i = 1, 2, 3$

z_i	recovery rate for remanufactured products of quality i where $i = 1, 2, 3$
f	proportion of expected processing time of the manufacturing operation over the expected processing time for the remanufacturing process
ω	proportional difference of remanufacturing processing times

Cost Parameters:

RW	expected raw material arrival rate
R	expected returned products arrival rate
π_{r_i}	expected remanufacturing processing time for returned products of quality i where $i = 1, 2, 3$
π_m	expected manufacturing processing time
π_a	expected assembly processing time
ν_{r_i}	average rate of remanufactured products for returned products of quality i where $i = 1, 2, 3$
ν_m	average rate of manufactured products
ν_a	average rate of assembled products
NDO_i	average rate of operational disposals from remanufacturing process for returned products of quality i where $i = 1, 2, 3$
NQ_j	expected number in the j^{th} queue where $j = 1, 2, ...8$
NQ_{fps}	expected number in the FPS
N_b	expected number of backorders
ND_{fps}	average rate of end stock disposals

Cost Values:

C_{RW}	raw material purchasing cost per unit

C_R	returned product purchasing cost per unit
CP_{r_i}	remanufacturing cost per time for return product of quality i where $i = 1, 2, 3$
CP_m	manufacturing cost per time
CP_a	assembly cost per time
CDO_i	operational disposal cost per unit for returned products of quality i where $i = 1, 2, 3$
CH_j	holding cost per unit/time for the number in the j^{th} queue where $j = 1, 2, ...8$
CH_{fps}	finished parts holding cost per unit/time
C_b	backorder cost per unit
CD_{fps_r}	end stock disposal cost per unit for remanufactured products
CD_{fps_m}	end stock cost disposal per unit for manufactured products

Control Variable:

K	FPS capacity

Objective Function:

$$
\begin{aligned}
TC &= (C_{RW} \times RW) + (C_R \times R) \\
&+ \sum_{i=1}^{3}(CP_{r_i} \times \pi_{r_i} \times \nu_{r_i}) + (CP_m \times \pi_m \times \nu_m) \\
&+ (CP_a \times \pi_a \times \nu_a) + \sum_{i=1}^{3}(CDO_i \times NDO_i) \\
&+ \sum_{j=1}^{8}(CH_j \times NQ_j) + (CH_{fps} \times NQ_{fps}) + (C_b \times N_b) \\
&+ (CD_{fps_r} \times ND_{fps} \times \frac{r\gamma \sum_{i=1}^{3}(z_i k_i)}{\lambda}) \\
&+ (CD_{fps_m} \times ND_{fps} \times \frac{\lambda - r\gamma \sum_{i=1}^{3}(z_i k_i)}{\lambda})
\end{aligned}
$$

In this model and all the subsequent models we use the following assumptions. Firstly, the demand follows an independent Poisson process with parameter γ. We assume that the arrival rate of system (λ) is also Poisson and greater than the demand rate. The returned product arrival rate is determined as the proportion of demand rate ($r\gamma$). The returned product arrival rate must always be smaller than the demand rate since at most all the satisfied demand can return to the system (Equation 3.1).

$$R = r\gamma \tag{4.1}$$

The average throughput rate of the manufacturing stage accounts for the difference between the total forecasted arrival rate of the system and the expected throughput of the remanufacturing process.

$$RW = (\lambda - r\gamma \sum_{i=1}^{3} (z_i k_i)) \tag{4.2}$$

We want the system to work at an average utilization (ρ_{avg}). We choose the maximum return rate of the returned products (r_{max}) considering Equation 3.1 and fix processing times of operations with respect to ρ_{avg} and r_{max}. All the processing times are assumed to be exponentially distributed. Remanufacturing processing times differ due to quality level of returns. The parameter ω represents the relative difference of remanufacturing processing times within quality levels. Hence,

$$\begin{aligned}
\pi_{r_2} &= \frac{\rho_{avg}}{r_{max}\gamma} \\
\omega &= \frac{\pi_{r_2}}{\pi_{r_1}} \\
\pi_{r_3} &= \pi_{r_2} + (\pi_{r_2} - \pi_{r_1})
\end{aligned}$$

The throughput rate of the remanufacturing operation for different quality returned products are calculated as below;

$$\nu_{r_i} = r\gamma k_i, i = 1, 2, 3$$

We use a parameter f which stands for the proportion of expected processing time of the manufacturing operation over the expected processing time for the remanufacturing process for returned product of average quality.

$$f = \frac{\pi_m}{\pi_{r_2}}$$

The throughput rate of the manufacturing operation is calculated as below;

$$\nu_m = (\lambda - r\gamma \sum_{i=1}^{3}(z_i k_i))$$

Arrival rate of the assembly process equals to the summation of total throughput of manufacturing operation and total throughput of the remanufacturing operation after operational disposals. And the throughput rate of the assembly operation is as below;

$$\nu_a = (\lambda - r\gamma \sum_{i=1}^{3}(z_i k_i)) + (r\gamma \sum_{i=1}^{3}(z_i k_i))$$
$$\nu_a = \lambda$$

Assembly processing time is calculated considering the average utilization of the system,

$$\pi_a = \frac{\rho_{avg}}{\lambda}$$

Average rate of operational disposals from remanufacturing process for return product of quality i is calculated due to material recovery rates for different quality levels of returned products.

$$NDO_i = r\gamma k_i(1 - z_i) \tag{4.3}$$

Expected number in $M/M/1/\infty$ queues at steady state (NQ_j) are calculated as below [30].

$$\rho_m = \nu_m \times \pi_m$$
$$NQ_1 = \frac{\rho_m^2}{1-\rho_m}$$

We assume remanufacturing processing time (π_r) is equal to the weighted average of the respective processing times of the returned products of quality i for simplification in calculations and remanufacturing expected number in the queue (NQ_r) is calculated according to this processing time. We also assume that there is no priority among remanufacturing queues.

$$NQ_2 = k_1 \times NQ_r$$
$$NQ_3 = k_2 \times NQ_r$$
$$NQ_4 = k_3 \times NQ_r$$

Assembly expected number in queue (NQ_a) is calculated according to (π_a) and related NQ_j are approximated as below. We assume that there is no priority among assembly queues.

$$\lambda = \nu_m + \nu_{r_1} + \nu_{r_2} + \nu_{r_3}$$
$$NQ_5 = \frac{\nu_m}{\lambda} \times NQ_a$$
$$NQ_6 = \frac{\nu_{r_1}}{\lambda} \times z_1 \times NQ_a$$
$$NQ_7 = \frac{\nu_{r_2}}{\lambda} \times z_2 \times NQ_a$$
$$NQ_8 = \frac{\nu_{r_3}}{\lambda} \times z_3 \times NQ_a$$

After the assembly operation products are sent to the finished parts storage (FPS) in order to meet the arriving demand, where unsatisfied demand is queued in B as a backorder. Here we model Sales (S) as a synchronization station fed by two Markovian arrival processes, respectively throughput of the system and demand arrivals, with arrival rates λ_{fps} and γ. Here finished parts storage has a capacity K and backorder queue has no capacity (Figure 4.2).

The throughput rate of the system is represented as λ_{fps} and equals to the total throughput rate of the last station which is assembly station in the system.

$$\lambda_{fps} \quad = \quad (\lambda - r\gamma \sum_{i=1}^{3}(z_i k_i)) + (r\gamma \sum_{i=1}^{3}(z_i k_i))$$

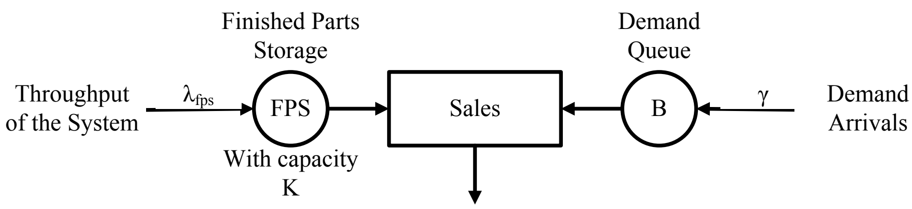

Figure 4.2. Synchronization station

We constructed the underlying Continuous Time Markov Chain (CTMC) as below, (Figure 4.3) [31]. The state of this CTMC is (n_1, n_2), where n_1 is currently present number in the FPS and n_2 is currently present number of backorders in the synchronization station.

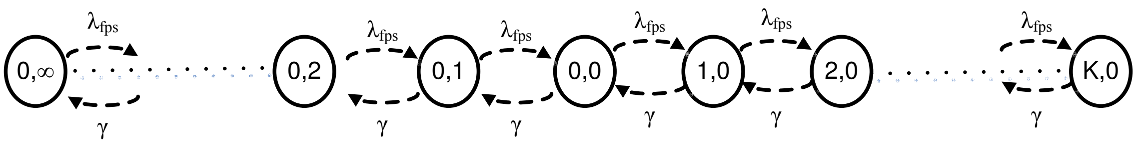

Figure 4.3. CTMC of a synchronization station

The equations for the steady state probabilities exist for $\lambda_{fps} > \gamma$ and are given as below:

$$\begin{aligned} P00 &= [(1/(1 - (\frac{\gamma}{\lambda_{fps}}))) + \sum_{n_1=1}^{K}(\frac{\lambda_{fps}^{n_1}}{\gamma^{n_1}})]^{-1} \\ P[0] &= P00 \times (1/(1 - (\frac{\gamma}{\lambda_{fps}}))) \\ P[n_1] &= P00 \times (\frac{\lambda_{fps}}{\gamma})^{n_1} \end{aligned}$$

We can calculate expected number in the FPS and expected number of backorders by using the above formula.

$$NQ_{fps} = \sum_{n_1=0}^{K}(n_1 P[n_1]) \quad (4.4)$$

$$N_b = P[0]\frac{1}{\frac{\lambda_{fps}}{\gamma}-1} \quad (4.5)$$

$$ND_{fps} = \lambda_{fps} \times P[K] \quad (4.6)$$

We used the following assumptions while assigning the cost values;

- $C_{RW} < C_R$
- $CP_{r_1} \leq CP_{r_2} \leq CP_{r_3} < CP_m$
- $CDO_1 \geq CDO_2 \geq CDO_3$

We assigned different cost values for the end stock from remanufactured parts (CD_{fps_r}) and from manufactured parts (CD_{fps_m}).

We adopted the traditional average cost (AC) approach in modeling the holding costs [32]. Here h represents the out-of-pocket holding cost rate and α represents the opportunity cost of capital. All of the holding costs are calculated as out-of-pocket holding cost rate plus the opportunity cost of capital times total cost incurred by the products held at the designated queue.

$$CH_1 = h + \alpha C_{RW}$$

$$CH_2 = h + \alpha C_R$$

$$CH_2 = CH_3 = CH_4$$

$$CH_5 = h + \alpha(C_{RW} + CP_m \pi_m)$$

$$CH_6 = h + \alpha(C_R + CP_{r_1}\pi_{r_1})$$

$$CH_7 = h + \alpha(C_R + CP_{r_2}\pi_{r_2})$$

$$CH_8 = h + \alpha(C_R + CP_{r_3}\pi_{r_3})$$

$$
\begin{aligned}
CH_{fps} &= h + \alpha((C_{RW} + CP_m\pi_m)(\nu_m/\nu_a) \\
&+ \sum_{i=1}^{3}((C_R + CP_{r_i}\pi_{r_i})((\nu_{r_i}z_i)/\nu_a)) \\
&+ (CP_a\pi_a))
\end{aligned}
$$

4.2. Numerical Analysis

In order to analyze the effects of the system parameters on the TC we constructed $6 \times 5 \times 2 \times 6 \times 5$ full factorial design (Table 4.1).

Table 4.1. Experimental design of system parameters

Factor	Name	Levels
A	r	0.7/0.75/0.8/0.85/0.9/0.95
B	$k_1 - k_2 - k_3$	0.8-0.1-0.1/0.5-0.3-0.2/0.1-0.8-0.1/0.2-0.3-0.5/0.1-0.1-0.8
C	$z_1 - z_2 - z_3$	0.9-0.6-0.3/0.9-0.7-0.5
D	f	1/1.2/1.4/1.6/1.8/2
E	ω	1.2/1.4/1.6/1.8/2

We use Design Expert 7.02 to construct the experimental design. We assume that arrival rate to the system equals to 1 and demand rate equals to 0.95. We want the system to work at an average utilization (ρ_{avg}) equal to 0.8 and we choose the maximum return rate of the returned products (r_{max}) as 1. Following cost values are used in the analysis.

Table 4.2. Cost values

Cost values		Cost values	
C_{RW}	0.1	CDO_i	1
C_R	1	CD_{fps_r}	5
CP_{r_i}	1	CD_{fps_m}	-0.1
CP_m	10	CP_a	1

We choose holding cost parameters as h equals to 0.01 and α equals to 0.05.

Backorder cost per unit (C_b) is assumed to have twice the value of FPS holding cost per unit/time (CH_{fps}).

After setting all the variables of the cost function we find the local optimum value of the inventory control variable (K) which minimizes the objective function (TC). Here when we assign a low value to K, expected number in the FPS decreases. However on the other hand at smaller values of K expected number of backorders in the system increase and vice versa. The increase of expected number in FPS also increases the total holding cost of numbers in this storage and increasing bacorders increase the backorder cost. We must search for a best value of K which balances the total finished parts holding cost with total backorder cost. We use a brute-force search method for the values of K from 1 to 100 and observe that the minimum TC is obtained for the control variable value of 21 in our experiments (Figure 4.4). This value is only depending on the λ_{fps} and γ. Therefore, the best value of the control variable is unique for all experiments. We assigned 21 to the value of K in our experiments.

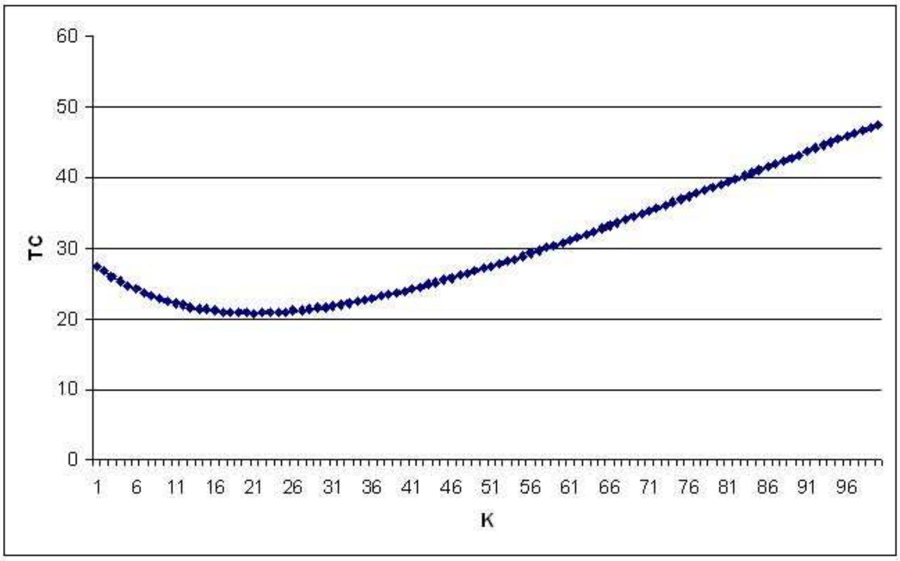

Figure 4.4. Effect of K on TC

We can analyze factor effects from the chart below. Figure 4.5 represents the TC values for the return arrival probabilities of 0.8-0.1-0.1. Here the great proportion of returns include good quality returns. TC decreases as the return rate increases because the unit cost of remanufacturing a product is cheaper than manufacturing.

The increase in f causes an increase in TC, because of the increasing manufacturing processing time with f. As the manufacturing processing time increases unit manufacturing cost also increases. As ω increases, TC decreases because the increase of ω causes a decrease in the remanufacturing processing time of the good quality returned products. Consequently remanufacturing cost also decreases. When we increase material recovery rates TC decreases. Higher recovery rates result with higher throughput of remanufactured products which causes a decrease in the TC. Figure 4.6 presents the TC values for the return arrival probabilities of 0.5-0.3-0.2. This case shows similarities with the case 0.8-0.1-0.1.

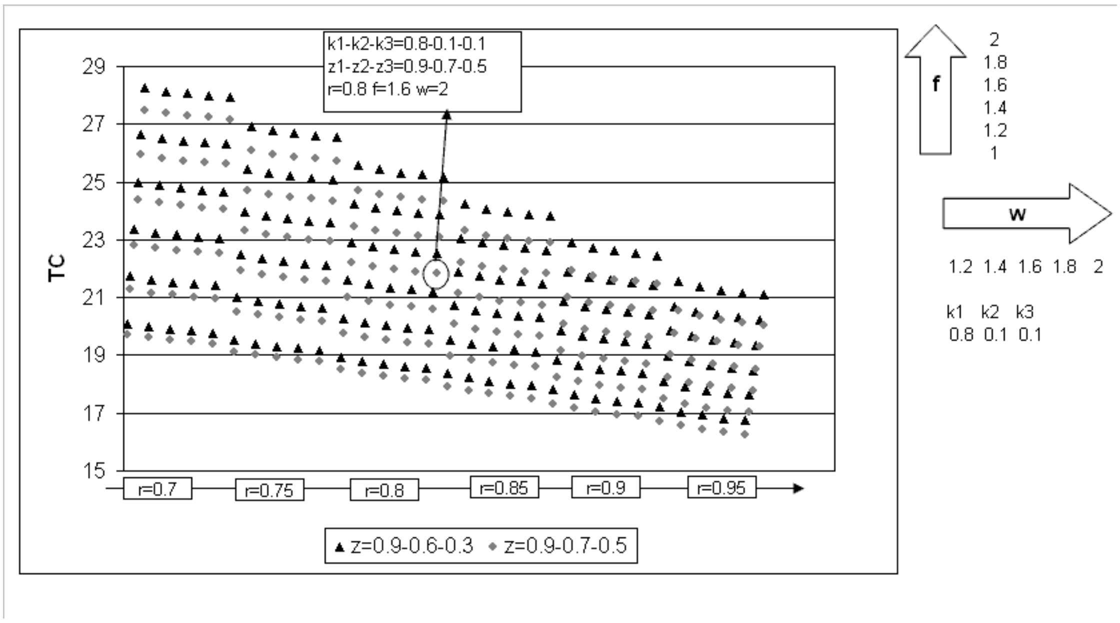

Figure 4.5. Factor effects for $k_1 - k_2 - k_3 = 0.8 - 0.1 - 0.1$

For the case of which the great proportion of returns include average quality returns (Figure 4.7), ω has no more effect on TC. The parameter ω represents the proportional difference of remanufacturing processing times. When the system mostly includes average quality returns in the returned products mix, the proportional dif-

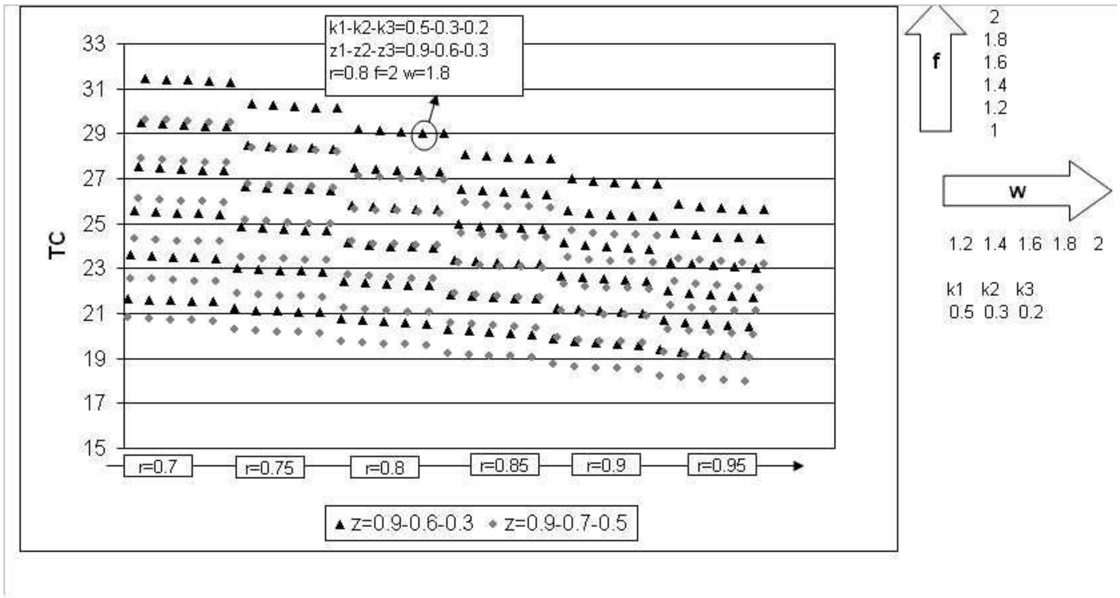

Figure 4.6. Factor effects for $k_1 - k_2 - k_3 = 0.5 - 0.3 - 0.2$

ference of remanufacturing processing times have an insignificant effect on the TC. Because by the factor ω we find the remanufacturing processing time of good quality and bad quality returned products over average quality returned products. In a situation where the great proportion of returns include average quality returns, the effect of ω decreases.

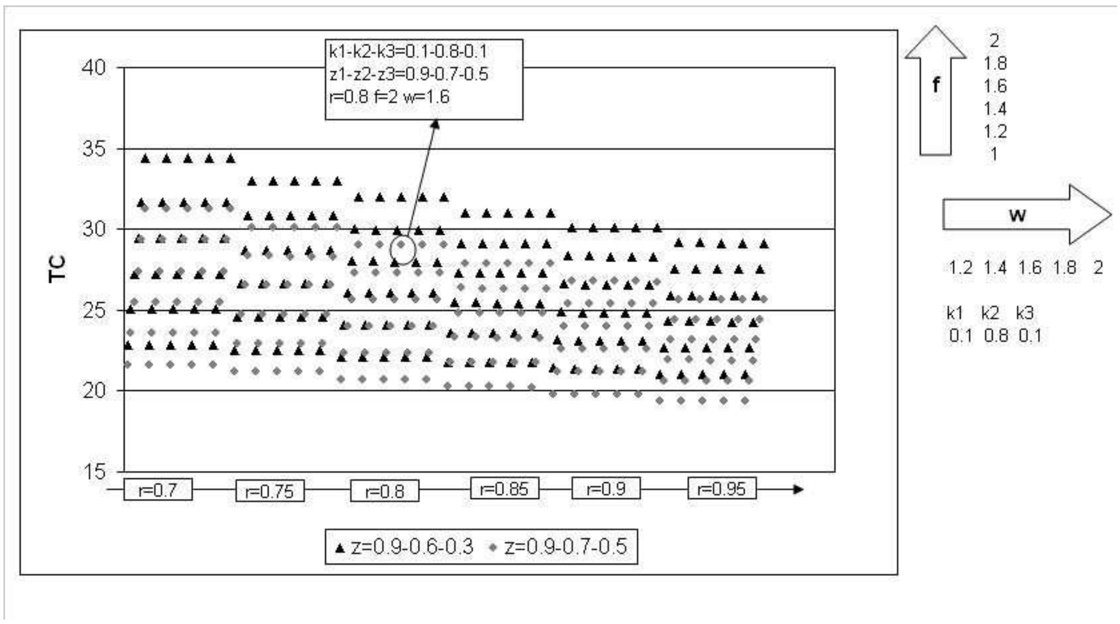

Figure 4.7. Factor effects for $k_1 - k_2 - k_3 = 0.1 - 0.8 - 0.1$

In Figure 4.8 half of the return arrivals is composed of bad quality returns, hence the system tends to manufacture more than the cases above to balance the system throughput with demand. However, manufacturing capacity is exceeded at some factor combinations seen on the Figure 4.8. Figure 4.9 represents the TC values for the return arrival probabilities of 0.1-0.1-0.8. Here the great proportion of returns include bad quality returns which causes a TC increase. The manufacturing capacity problem is also seen in this case for much more of the factor combinations. Because of the longer remanufacturing processing times of bad quality returns remanufacturing capacity is also exceeded in some cases.

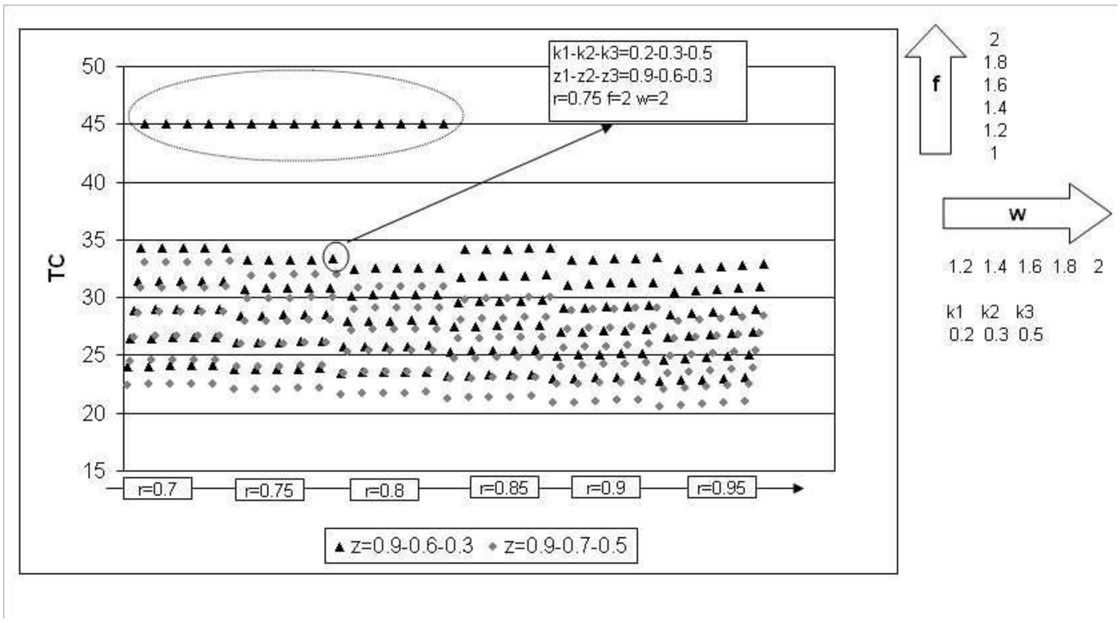

Figure 4.8. Factor effects for $k_1 - k_2 - k_3 = 0.2 - 0.3 - 0.5$

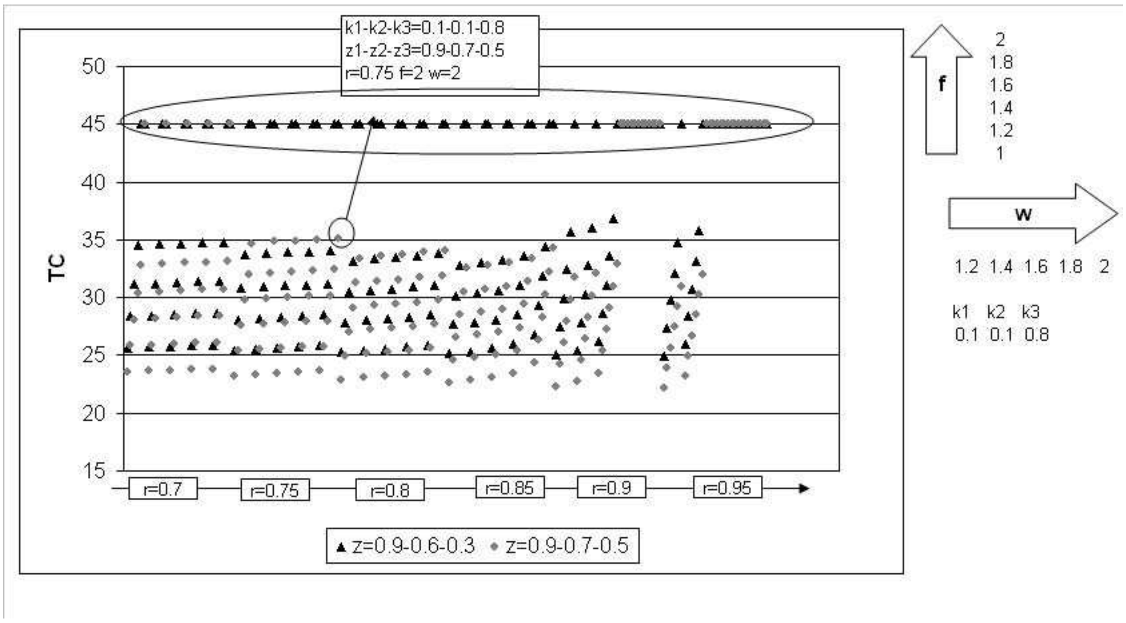

Figure 4.9. Factor effects for $k_1 - k_2 - k_3 = 0.1 - 0.1 - 0.8$

4.3. Conclusion

Experimental analysis show us that TC decreases as the return rate increases, the increase of f causes an increase on TC and as ω increases TC decreases in most of the cases. However in the cases where the proportion of bad quality arrivals are greater than others (0.2-0.3-0.5 and 0.1-0.1-0.8 cases) there could happen some capacity problems with manufacturing and remanufacturing processes. We offer to increase related capacities in these cases or to use capacitated queues to decrease the queue lenghts. In order to solve these problems we used capacitated queues in the next models.

The outputs of the analysis show that the most important factor affecting TC is probability of return arrivals (k_i) with 45 per cent contribution, second factor is expected processing time of the manufacturing operation relative to the expected processsing time for the remanufacturing process (f) with 36 per cent contributon, other factors as proportion of return rate (r) and material recovery rates for remanufactured products (z_i) have effects with contributions respectively 4 per cent and 5 per cent and relative difference of remanufacturing processing times (ω) does not seem to have any important effect on TC with 0.1 per cent contribution (Table 4.3).

Table 4.3. Per cent contributions of factors

Term	DOF	SumSqr	% Contribution
A-r	5	1850.164131	3.98080749
B-$k_1 - k_2 - k_3$	4	20986.31965	45.15410123
C-$z_1 - z_2 - z_3$	1	2459.471662	5.291791712
D-f	5	16993.79518	36.56379777
E-ω	4	50.20616369	0.108023428
AB	20	1077.882816	2.319169372
AC	5	17.65077035	0.037977344
AD	25	286.4420037	0.61630774
AE	20	98.65158141	0.212258441
BC	4	649.4947305	1.397450877
BD	20	1010.137274	2.17340827
BE	16	303.2481401	0.652467771
CD	5	200.329914	0.431029231
CE	4	0.021199517	4.56128E-05
DE	20	0	0

5. MULTI STAGE INVENTORY CONTROL WITH BLOCKING

In the following models we will use the classifying information in managing the inventory buffers and deciding on the blocking limits.

5.1. Model-2

This model uses blocking mechanism for the control of inventory levels at every stage in the system.

5.1.1. Problem Definition

In this thesis different from the previous remanufacturing literature we classify returned products into three quality levels in order to analyze the impact of quality uncertainty of returns. If we do not classify returns, we cannot accurately forecast expected raw material arrival rates and this can result in inaccurate TC calculations. By classifying we can place returns of different quality levels into different remanufacturing and assembly queues. This way we can assign different holding cost values to these products. Classifying returned products also enables us to give different blocking limits to different remanufactured parts of quality i buffers.

In this model we use blocking mechanism in order to control buffer sizes. The blocking mechanism works with 'block after service' (BAS) principle. In this principle when an item is ready to join a station, if the buffer of the station is not full then the item joins the queue at that station else if the buffer of the station is full then the item cannot join the queue and stays where it is originated from and blocks that server. A blocked item is released from the up station when the buffer of downstream station becomes available.

When a demand occurs we check the FPS, if a finished product is available then demand is satisfied with this product. If we do not satisfy demand, then a backorder occurs. As an addition to the previous model there is a backorder capacity in the system (B). When this capacity is reached subsequent orders are rejected and recorded as lost sales. FPS has a capacity (K), when the finished products storage reaches this limit then the assembly station is blocked until FPS becomes empty. The blockage of the assembly station increases the numbers of the parts in the downstream buffers of this station. Assembly station has four downstream buffers which are manufactured parts buffer, remanufactured parts of quality 1 buffer, remanufactured parts of quality 2 buffer and remanufactured parts of quality 3 buffer. These buffers have capacities respectively $K5$, $K6$, $K7$ and $K8$ which cause the blockage of downstream stations. When the manufacturing station is blocked, the number in the raw materials buffer increases. This buffer has a capacity $K1$, when this buffer becomes full then the incoming raw materials cannot enter the buffer and are considered lost without increasing any costs. When the remanufacturing station is blocked, the returned product numbers in the downstream buffers increase. These buffers have the respective capacities, $K2$, $K3$ and $K4$. In the case of reaching the capacity limits of these buffers incoming returned products can not enter these buffers and the arriving returns are disposed of with different disposal costs for different quality typed returned products, (Figure 5.1).

The system parameters, cost parameters and cost values are the same as in Section 4.1 with the following additions.

Cost Parameters:

ND_j	average rate of overflow disposals from buffer j where $j = 1, 2, 3, 4$

Cost Values:

CD_j	overflow disposal cost per unit for overflows from buffer j where $j = 1, 2, 3, 4$

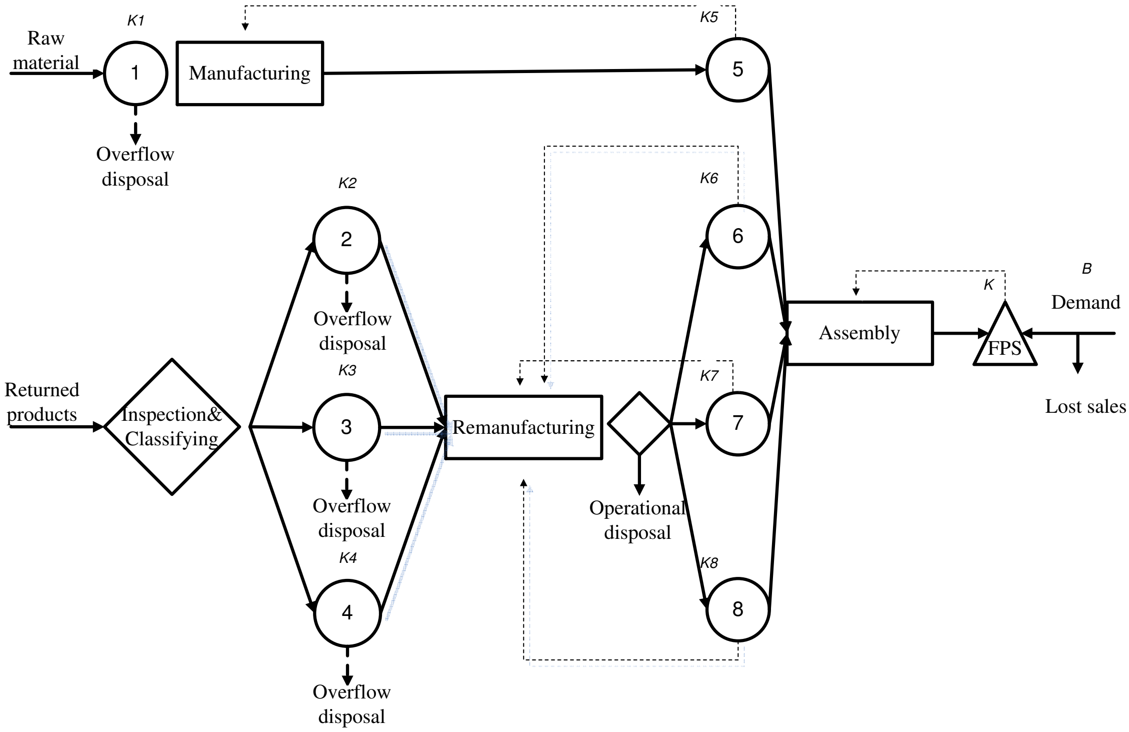

Figure 5.1. Model-2

Control Variables:

K_j	Buffer capacity for buffer j where $j = 1, 2, 3, 4$
K_j	Blocking limit for buffer j where $j = 5, 6, 7, 8$
K	Blocking limit for FPS
B	Backorder capacity

Objective Function:

$$
\begin{aligned}
TC &= (C_{RW} \times RW) + (C_R \times R) \\
&+ \sum_{i=1}^{3}(CP_{r_i} \times \pi_{r_i} \times \nu_{r_i}) + (CP_m \times \pi_m \times \nu_m) \\
&+ (CP_a \times \pi_a \times \nu_a) + \sum_{i=1}^{3}(CDO_i \times NDO_i) \\
&+ \sum_{j=1}^{8}(CD_j \times ND_j) \\
&+ \sum_{j=1}^{8}(CH_j \times NQ_j) + (CH_{fps} \times NQ_{fps}) + (C_b \times N_b) \\
&+ (C_{ls} \times N_{ls})
\end{aligned}
$$

Here, different from Model-1 overflow disposals occur from the buffers 1,2,3,4. We assume that overflow disposals from manufacturing buffer are directly sent to raw material supplier with the salvage value equals to the raw material purchasing cost. However, remanufacturing overflow disposals have a penalty cost.

$$
\begin{aligned}
CD_1 &= -C_{RW} \\
CD_2 &\geq CD_3 \geq CD_4
\end{aligned}
$$

5.1.2. Simulation

Here we choose the experiments from the full factorial design represented in Section 4.2 which give us the maximum TC, as given in Table 5.2. Since simulating all the experiments of full factorial design requires too much time. A set of experiments that represent the general trend of the whole system are selected. In this model we have a total of 10 control variables and we construct a simulation model to find the best values of these control variables minimizing the total cost of our system.

The cost values used in the simulation model are as given in table 5.1:

Table 5.1. Cost values

Cost values		Cost values	
C_{RW}	0.1	CDO_i	1
C_R	1	C_{ls}	50
CP_{r_i}	1	CD_1	-0.1
CP_m	10	$CD_2 = CD_3 = CD_4$	5
CP_a	5		
h	0.01	α	0.05

The simulation program Arena 9.0 is used for the implementation of the simulation model of multi stage inventory control. Within this program, each experiment is simulated for 36 000 minutes and replicated 30 times. The first 6000 minutes of each replication are set as the warm-up period. Thus the statistics are calculated for 30 000 minutes in each replication. The length of the warm-up period was chosen by using the Welch procedure [33]. We analyzed the average number of queue lengths by the Welch procedure and found the time at which the average number of queue lengths reach steady state. We observed that 6000 minutes is more than adequate for the queue lengths to reach steady state. The common random numbers are used in the simulation in order to have identical experiments for each replication and to reduce the experiment-wise error.

Arena 9.0 simulation program gives the half width results in the output report files. If a value is returned in the half width category, this value may be interpreted by saying ‘ in 95 per cent of repeated trials, the sample mean would be reported as within the interval sample mean half width’. The half width can be reduced by increasing the number of replications. The 30 replications and long simulation runs provide accurate results.

Table 5.2. Simulated experiments

Experiments	λ	γ	r	k_1	k_2	k_3	z_1	z_2	z_3	f	ω
1	1	0.95	0.7	0.8	0.1	0.1	0.9	0.6	0.3	2	2
2	1	0.95	0.8	0.8	0.1	0.1	0.9	0.6	0.3	2	2
3	1	0.95	0.9	0.8	0.1	0.1	0.9	0.6	0.3	2	2
4	1	0.95	0.7	0.5	0.3	0.2	0.9	0.6	0.3	2	2
5	1	0.95	0.8	0.5	0.3	0.2	0.9	0.6	0.3	2	2
6	1	0.95	0.9	0.5	0.3	0.2	0.9	0.6	0.3	2	2
7	1	0.95	0.7	0.1	0.8	0.1	0.9	0.6	0.3	2	2
8	1	0.95	0.8	0.1	0.8	0.1	0.9	0.6	0.3	2	2
9	1	0.95	0.9	0.1	0.8	0.1	0.9	0.6	0.3	2	2
10	1	0.95	0.7	0.2	0.3	0.5	0.9	0.6	0.3	2	2
11	1	0.95	0.8	0.2	0.3	0.5	0.9	0.6	0.3	2	2
12	1	0.95	0.9	0.2	0.3	0.5	0.9	0.6	0.3	2	2
13	1	0.95	0.7	0.1	0.1	0.8	0.9	0.6	0.3	2	2
14	1	0.95	0.8	0.1	0.1	0.8	0.9	0.6	0.3	2	2
15	1	0.95	0.9	0.1	0.1	0.8	0.9	0.6	0.3	2	2
16	1	0.95	0.7	0.8	0.1	0.1	0.9	0.7	0.5	2	2
17	1	0.95	0.8	0.8	0.1	0.1	0.9	0.7	0.5	2	2
18	1	0.95	0.9	0.8	0.1	0.1	0.9	0.7	0.5	2	2
19	1	0.95	0.7	0.5	0.3	0.2	0.9	0.7	0.5	2	2
20	1	0.95	0.8	0.5	0.3	0.2	0.9	0.7	0.5	2	2
21	1	0.95	0.9	0.5	0.3	0.2	0.9	0.7	0.5	2	2
22	1	0.95	0.7	0.1	0.8	0.1	0.9	0.7	0.5	2	2
23	1	0.95	0.8	0.1	0.8	0.1	0.9	0.7	0.5	2	2
24	1	0.95	0.9	0.1	0.8	0.1	0.9	0.7	0.5	2	2
25	1	0.95	0.7	0.2	0.3	0.5	0.9	0.7	0.5	2	2
26	1	0.95	0.8	0.2	0.3	0.5	0.9	0.7	0.5	2	2
27	1	0.95	0.9	0.2	0.3	0.5	0.9	0.7	0.5	2	2
28	1	0.95	0.7	0.1	0.1	0.8	0.9	0.7	0.5	2	2
29	1	0.95	0.8	0.1	0.1	0.8	0.9	0.7	0.5	2	2
30	1	0.95	0.9	0.1	0.1	0.8	0.9	0.7	0.5	2	2

5.1.3. Verification and validation of the model

After the implementation of the simulation model of multi stage inventory control with blocking by modeling the processes, queues, disposals and arrivals under the above described assumptions and through exercising the basic process modules, elements and blocks of Arena 9.0, the verification and validation of the model are conducted.

Verification is determining that a simulation computer program performs as intended, i.e. debugging the computer model. In this study we used the techniques that can be used to debug the computer program of a simulation model proposed by Law and Kelton [33]. In order to verify the simulation model, we decomposed our model and debugged in modules. Since we analyze different parameter sets and experiments we ran the simulation under a variety of these settings and observed the output values. We compared the output of the simulation model under different settings with the previous analytical model outputs and observed that the output of the simulation model is reasonable. One of the most powerful techniques, that can be used to debug a discrete-event simulation program is a trace. In a trace, the state of the simulated system is printed out just after each event occurs. We analyzed the trace of our simulation model and compared the outputs with the hand calculations and observed that the program is operating as intended. Also we animated the simulation model in order to observe the simulation output.

After the verification of the model is completed and the model is run by the input data, the outputs are collected and the validation step is initiated. Validation is concerned with determining whether the simulation model is an accurate representation of the system under study. We refer to the authors Naylor and Finger [34], where a three-step approach is given for validating a simulation model.

The first step of the validation process is to develop a model with high face validity which means to construct a model that seems reasonable to people who are knowledgeable about the system under study. For this reason we get the aid of expert people in this subject showed us that our simulation model is reasonable. In the second step of validation one of the most useful tool is the sensitivity analysis. This can be used to determine if the simulation output changes significantly when the value of an input parameter is changed. While implementing the sensitivity analysis we used common random numbers to control the randomness in the simulation. We used Design Expert 7.02 to construct the experimental design and analyzed the effects of the factors, eg. we expect a decrease in the TC with the increase of r as we observed from the single stage inventory control model and our simulation outputs gave the expected relation. The third step of the validation process is to establish that the simulation model's output data closely resembles the output data that would be expected from the actual system. However there is not an actual system similar to the model we simulated. Therefore the validation of the simulation model has been limited to what has been done in the literature.

5.1.4. Optimization of the control variables

In the previous sections the simulation model of the multi stage inventory control with blocking problem is constructed, run time, warm-up period, replication numbers are determined and model verification and validation is performed. We constructed this simulation model in order to optimize the inventory control variables which we defined in Section 5.1.1. Arena simulation program uses OptQuest as a simulation optimization method. OptQuest is a generic optimizer that successfully separates the method from the model [35]. In this case, the optimization problem is defined outside the complex system. This way, the simulation model can change and develop to incorporate additional elements of the complex system, while the optimization procedure remains the same. Hence, there is a complete separation between the model that represents the system and the procedure that is used to solve the optimization problem. OptQuest does allow the user to input problem structure through the use of constraints and has specialized mechanisms for analyzing specific types of problems.

OptQuest includes a highly efficient algorithm for the optimization process. The optimization procedure uses the outputs from the simulation model to evaluate the inputs to the model. Analyzing this evaluation and previous evaluations, the optimization procedure selects a new set of input values, (Figure 5.2).

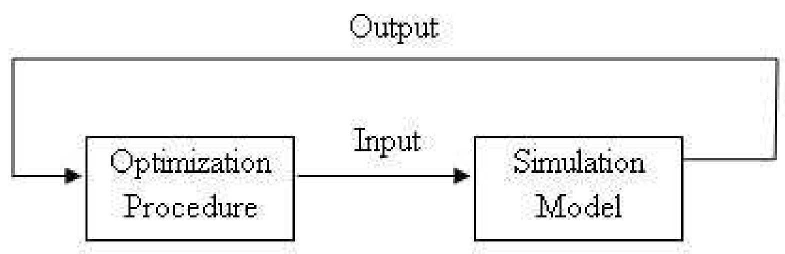

Figure 5.2. Coordination between optimization and system evaluation

In the optimization procedure a ‘ non-monotonic search ’ is used. In this search algorithm successively generated inputs produce varying evaluations, not all of them improving, but which over time provide a highly efficient route to the best solutions. The process continues until an appropriate termination criterion is satisfied. This non-monotonic search algorithm is a special combination of tabu search and scatter search. Scatter search operates on a set of points, called reference points, that result in good solutions. The approach systematically generates linear combinations of the reference points to create new points, each of which maps into an associated point that yields integer values for discrete variables. Tabu search is then superimposed to control the composition of reference points in each stage [35].

Tabu search uses memory concept by which the search history guides the process. Using memory excludes the search from repeatedly investigating the solutions that have already been evaluated. However, the use of memory in OptQuest is much more complex and uses memory functions to encourage search diversification and intensification. These memory components let the search escape from locally optimal solutions to find a global optimal solution [35].

Scatter search is an information-driven approach, developing knowledge obtained from the search space, high-quality solutions found within the space, and routes through the space over time. The combinations of these factors creates a highly effective solution process. The incorporation of such designs gives OptQuest the ability to solve complex simulation based problems with high efficiency [35].

5.1.5. Outputs of the model

In this study, we used OptQuest to find the best values of inventory control variables for the chosen experiments of the multi stage inventory control with blocking models which minimizes the total cost of the system. We replicated each experiment 30 times and used a termination criterion for the optimization process which stops the search algorithm after 250 combinations. We choose 250 combinations for the termination criterion, because we observed that after 200 replications of each experiment with different control variables the total cost of the system does not change any further. Thus we simulated 250 different combinations of each experiment to get an appropriate total cost value.

We simulated the experiments with the defined parameters seen in Table 5.2. We set the upper values of the buffer capacities to 30. The OptQuest algorithm found the values for the control variables minimizing the TC, (Appendix A). When we analyzed the proposed values of the control variables minimizing TC, we noticed that there is on the average 37.705 per cent decrease in the TC among the chosen 30 experiments compared with the TC values found in model-1, (Table 5.3). The proposed values of the control variables indicate that giving lower values to the manufactured parts buffer capacity decreases the TC. The reason for this phenomenia is, when we assign lower values to the manufactured parts buffer capacity then we mainly block the manufacturing operation and dispose raw materials from the on hand inventory buffers. In this situation we produce more from the remanufactured parts and we can decrease the TC by this way. In all of the experiments we observed that this limit takes the value 1. And the other best limits for the control parameters change according to the scenarios.

Table 5.3. Comparison of Model-1 and Model-2

Ex.	TC**(model1)**	TC**(model2)**	**%decrease**
1	27.952	16.204	42.030
2	25.202	14.896	40.893
3	22.449	13.047	41.882
4	31.321	18.671	40.388
5	29.015	17.579	39.413
6	26.767	15.948	40.418
7	34.351	20.681	39.795
8	31.978	18.958	40.714
9	30.089	17.710	41.142
10	inf.	25.568	inf.
11	inf.	23.757	inf.
12	33.458	21.962	34.359
13	inf.	27.222	inf.
14	inf.	28.765	inf.
15	inf.	29.640	inf.
16	27.141	15.766	41.912
17	24.256	13.955	42.470
18	21.471	13.374	37.710
19	29.487	17.126	41.920
20	27.001	15.846	41.314
21	24.447	14.673	39.982
22	31.277	18.357	41.308
23	29.018	16.798	42.113
24	26.771	16.079	39.941
25	33.125	25.948	21.668
26	30.975	22.520	27.295
27	29.133	20.399	29.979
28	inf.	25.387	inf.
29	34.062	27.739	18.564
30	inf.	28.443	inf.

max decrease	42.470
avg decrease	37.705
min decrease	18.564

5.2. Model-3

This model uses blocking mechanism for the control of inventory levels at manufacturing stage in the system.

5.2.1. Problem Definition

In this model different from Model-2 we do not use blocking mechanism in the remanufacturing process. The blocking mechanism works with 'block after service' (BAS) principle. In this principle when an item is ready to join a station, if the buffer of the station is not full then the item joins the queue at that station else if the buffer of the station is full then the item cannot join the queue and stays where it is originated from and blocks that server. A blocked item is released from the downstream station when the buffer of upstream station becomes empty.

When a demand occurs we check the FPS, if a finished product is available then the demand is satisfied with this product. If we do not satisfy demand then a backorder occurs. There is a backorder capacity in the system (B), when this capacity is reached subsequent orders are rejected and recorded as lost sales. FPS has a capacity (K), when the finished products storage reaches this limit then the assembly station is blocked until FPS becomes empty. The blockage of the assembly station increases the numbers of the parts in the downstream buffers of this station. Assembly station has four downstream buffers which are manufactured parts buffer, remanufactured parts of quality 1 buffer, remanufactured parts of quality 2 buffer and remanufactured parts of quality 3 buffer. We assigned priority to remanufactured parts at the assembly stage in this model. Among these buffers only manufactured parts buffer has a capacity $K5$ which causes the blockage of manufacturing station in the case of reaching the buffer limit. Other buffers have infinite capacities since they have priority at assembly station and the waiting numbers in these buffers do not increase so much. When manufacturing station is blocked, the number in the raw materials buffer increases. This buffer has a capacity $K1$, when this buffer becomes full then the incoming raw materials can not enter the buffer and are considered lost. Also returned product buffers have the respective capacities, $K2$, $K3$ and $K4$. In the case of reaching the capacity limits of these buffers incoming returned products can not enter these buffers and they are considered lost, (Figure 5.3).

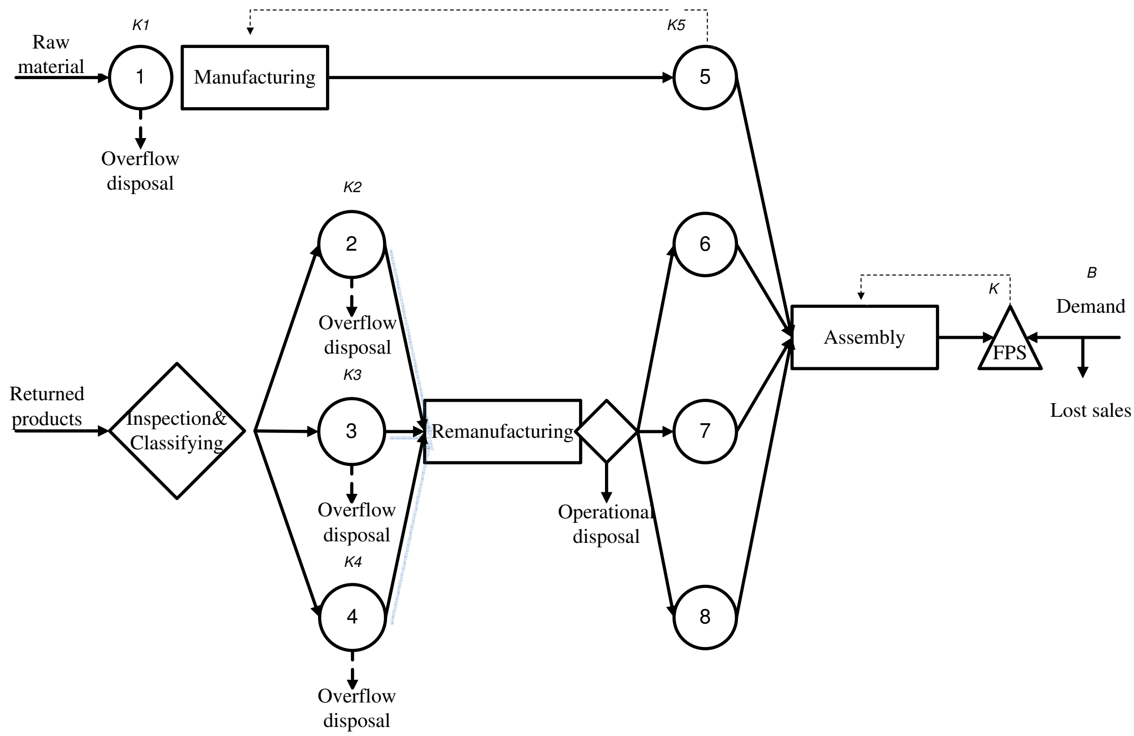

Figure 5.3. Model-3

Cost parameters are the same as in Model-2. The only difference is in $K6$, $K7$ and $K8$ where they are set to infinity.

Hence objective function is given as:

$$\begin{aligned} TC &= (C_{RW} \times RW) + (C_R \times R) \\ &+ \sum_{i=1}^{3} (CP_{r_i} \times \pi_{r_i} \times \nu_{r_i}) + (CP_m \times \pi_m \times \nu_m) \\ &+ (CP_a \times \pi_a \times \nu_a) + \sum_{i=1}^{3} (CDO_i \times NDO_i) \\ &+ \sum_{j=1}^{4} (CD_j \times ND_j) \\ &+ \sum_{j=1}^{8} (CH_j \times NQ_j) + (CH_{fps} \times NQ_{fps}) + (C_b \times N_b) \\ &+ (C_{ls} \times N_{ls}) \end{aligned}$$

5.2.2. Outputs of the model

In this model we simulated the same 30 experiments proposed in Section 5.1. Here we have a total of 7 control variables. We constructed a simulation model to find the best values of these control variables minimizing the total cost of our system. The constructed simulation model includes the same parameters and variables as the analytical model defined in Section 4.1 and the additional parameters, variables and values given in Section 5.1. The cost values used for the cost function in this section is proposed in Table 5.4.

Table 5.4. Cost values

Cost values		Cost values	
C_{RW}	0.1	CDO_i	1
C_R	1	C_{ls}	50
CP_{r_i}	1	CD_1	-0.1
CP_m	10	$CD_2 = CD_3 = CD_4$	5
CP_a	5		
h	0.01	α	0.05

The experimental setup is the same as in Model-2. We set the upper values of the buffer capacities to 30. OptQuest algorithm found the best values for the control variables minimizing the TC, (Appendix A). When we analyzed the proposed values of the control variables minimizing TC, we noticed that there is on the average 38.042 per cent decrease in the TC among the chosen 30 experiments compared with the TC values found in Model-1, (Table 5.5). We compared the TC values of Model-2 and Model-3 and observed that there is on the average 0.412 per cent decrease in the cost values by using Model-3 versus Model-2 (Table 5.6). We use a single control variable for the finished products storage capacity in Model-1. This model gives us maximum throughput from the system. However because of infinite queues the number of parts in the buffers are high and this position brings higher holding costs to the system. In Model-2 we use blocking mechanism at every stage in the system. This way we can control inventory levels and decrease holding costs. In Model-3 we use the blocking mechanism for only the manufacturing stage and use infinite queues for remanufacturing buffers before the assembly operation. In this model we give priority to the remanufactured parts at the assembly stage. Model-3 gives better TC values in most of the experiments. Because in this model we produce more of the remanufactured parts and blocking manufacturing parts enables us to dispose raw materials mainly, which brings us a cost decrease. Therefore we choose Model-3 for the sensitivity analysis in this thesis.

Table 5.5. Comparison of model-1 and model-3

Ex.	TC(**model1**)	TC(**model3**)	**%decrease**
1	27.952	16.310	41.651
2	25.202	14.828	41.165
3	22.449	13.417	40.231
4	31.321	18.344	41.431
5	29.015	17.016	41.354
6	26.767	16.005	40.206
7	34.351	21.006	38.849
8	31.978	18.961	40.705
9	30.089	17.816	40.789
10	inf.	25.645	inf.
11	inf.	23.914	inf.
12	33.458	21.206	36.618
13	inf.	27.393	inf.
14	inf.	28.711	inf.
15	inf.	29.354	inf.
16	27.141	15.598	42.529
17	24.256	14.146	41.680
18	21.471	12.983	39.532
19	29.487	17.426	40.904
20	27.001	15.845	41.315
21	24.447	14.593	40.309
22	31.277	18.093	38.955
23	29.018	16.930	41.657
24	26.771	15.969	40.350
25	33.125	24.832	25.036
26	30.975	22.610	27.004
27	29.133	20.693	28.968
28	inf.	25.099	inf.
29	34.062	27.069	20.531
30	inf.	28.092	inf.

max decrease	42.529
avg decrease	38.042
min decrease	20.531

Table 5.6. Comparison of model-2 and model-3

Ex.	TC**(model2)**	TC**(model3)**	**%decrease**
1	16.204	16.310	-0.654
2	14.896	14.828	0.460
3	13.047	13.417	-2.841
4	18.671	18.344	1.750
5	17.579	17.016	3.203
6	15.948	16.005	-0.356
7	20.681	21.006	-1.572
8	18.958	18.961	-0.015
9	17.710	17.816	-0.600
10	25.568	25.645	-0.301
11	23.757	23.914	-0.658
12	21.962	21.206	3.442
13	27.222	27.393	-0.628
14	28.765	28.711	0.188
15	29.640	29.354	0.964
16	15.766	15.598	1.062
17	13.955	14.146	-1.373
18	13.374	12.983	2.925
19	17.126	17.426	-1.748
20	15.846	15.845	0.000
21	14.673	14.593	0.546
22	18.357	18.093	1.438
23	16.798	16.930	-0.788
24	16.079	15.969	0.682
25	25.948	24.832	4.301
26	22.520	22.610	-0.401
27	20.399	20.693	-1.444
28	25.387	25.099	1.134
29	27.739	27.069	2.416
30	28.443	28.092	1.233

max decrease	4.301
avg decrease	0.412
min decrease	-2.841

5.3. Extension to General Distribution

In this section we extend the models by using general distributed remanufacturing processing times instead of exponential in order to reflect a more realistic hybrid system. We use lognormal distribution in our analysis and study under different standard deviations. In the general distribution cases we use the same cost structure as in the previous chapters. For the remanufacturing processing times we assign the mean processing times equal to the exponential model and calculate lognormal standard deviations as a multiplier (c) times mean of the distribution.

Standard deviation calculations for the lognormal distribution:

Mean of remanufacturing processing time for return product of quality 1 = π_{r_1} (Standard deviation = $c * \pi_{r_1}$)

Mean of remanufacturing processing time for return product of quality 2 = π_{r_2} (Standard deviation = $c * \pi_{r_2}$)

Mean of remanufacturing processing time for return product of quality 3 = π_{r_3} (Standard deviation = $c * \pi_{r_3}$)

In this study we used three different levels for multiplier c which are 0.5, 1 and 2. We simulated Model-1, Model-2 and Model-3 with the best control variables provided in the previous chapters by using lognormal distributed remanufacturing processing times and compared the TC values obtained by these simulation results with the exponential cases. From the simulation results we observed that when c=0.5, TC values decrease with respect to exponential models, when c=1 the TC values of exponential cases and lognormal cases get closer and when c=2 TC values obtained by lognormal cases exceed the exponential cases. The distribution of the remanufacturing processing times affects the queue lengths before this operation, with smaller variances queue lengths decrease and with higher variances queue lengths increase. The decrease in queue lengths decreases the holding costs and therefore decreases the total expected cost per unit (TC), while the increase of queue lengths has the opposite effect. The figures, Figure 5.4 to 5.6, show the per cent differences of TC values between the exponential and lognormal models for the chosen 30 experiments.

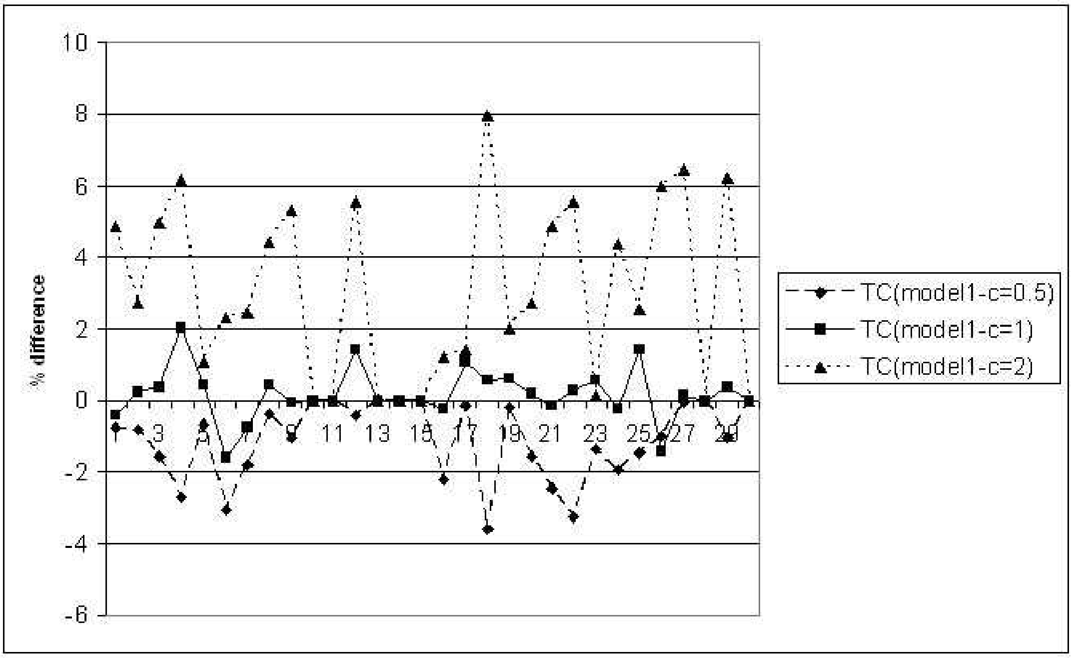

Figure 5.4. Per cent differences between exponential and lognormal cases

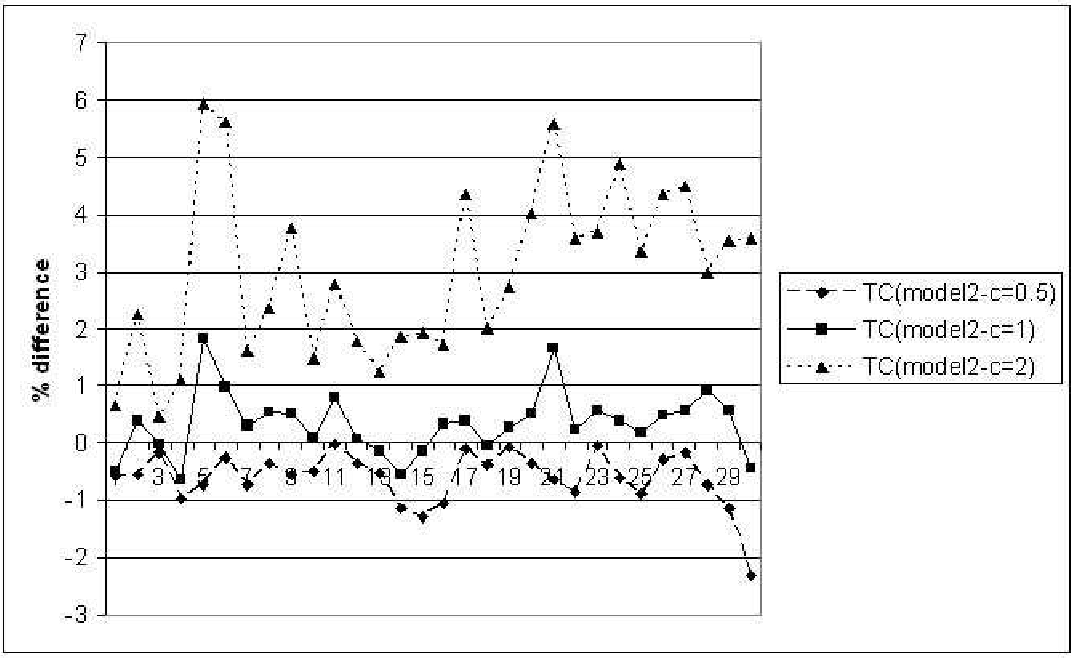

Figure 5.5. Per cent differences between exponential and lognormal cases

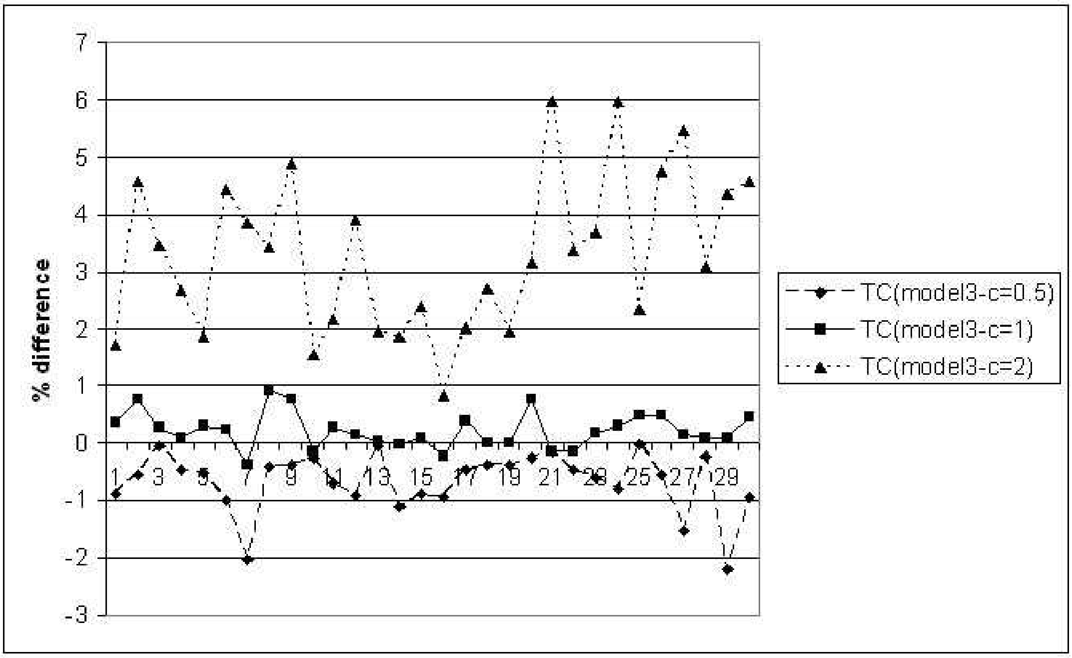

Figure 5.6. Per cent differences between exponential and lognormal cases

6. SENSITIVITY ANALYSIS

In this study we classify returned products into three quality levels in order to analyze the impact of quality uncertainty of returns. This classification enables us to assign different processing times and material recovery rates to different quality types of returned products. After determining the system parameters we assign the cost values and construct the cost function. Classification of returned products also enables us to assign different remanufacturing and disposal costs to returned products with different qualities.

In this chapter we construct a benchmark model which assumes no classification of returned products, in order to compare the TC values of the model with classification to the model with no classification. In the benchmark model we use the same properties of Model-3 but we do not classify returned products, (Figure 6.1).

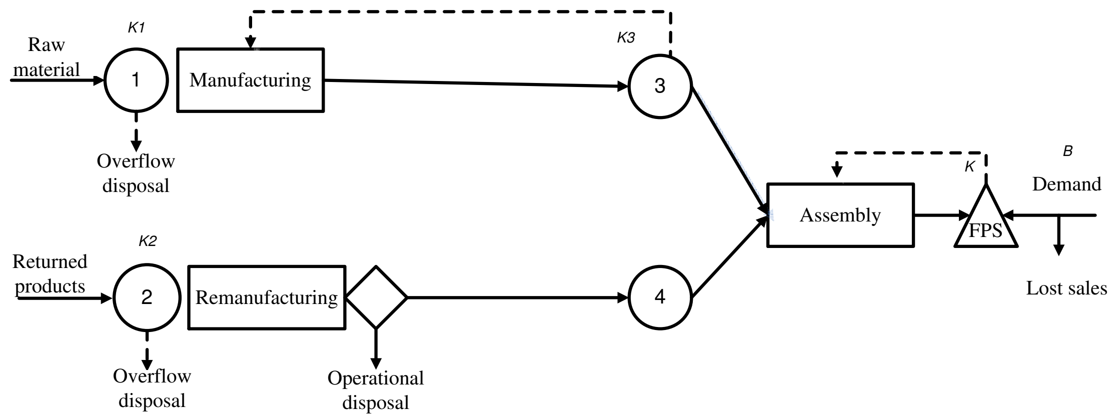

Figure 6.1. Benchmark model with no classification

In the benchmark model since returned products are not classified, we have only one queue for the returned products before remanufacturing operation including all qualities of returned products and for the remanufactured products before the assembly operation. We have an average remanufacturing processing time for all returned products and only one average material recovery rate for all returned products.

In the model with no classification (benchmark model), we use a single remanufacturing processing time for all returned products. This processing time is calculated as the weighted average of the processing times of different quality returned products.

$$\pi_r = (k_1 \times \pi_{r_1}) + (k_2 \times \pi_{r_2}) + (k_3 \times \pi_{r_3})$$

We also use a single material recovery rate for all typed returned products in the model with no classifying. Similar to the remanufacturing processing time, material recovery rate is calculated as the weighted average of the material recovery rates of different quality typed returned products.

$$z_r = (k_1 \times z_1) + (k_2 \times z_2) + (k_3 \times z_3)$$

In the previous models which considered classification of returned products according to quality levels, we could assign different remanufacturing processing and disposal costs to different type of returned products. However in this benchmark model we use a single remanufacturing processing cost and a single disposal costs for all returned products. For the remanufacturing processing cost we use the weighted average of the remanufacturing processing costs of different quality returned products.

$$CP_r = (k_1 \times CP_{r_1}) + (k_2 \times CP_{r_2}) + (k_3 \times CP_{r_3})$$

Operational disposal cost is calculated as following:

$$CDO_r = (k_1 \times CDO_1) + (k_2 \times CDO_2) + (k_3 \times CDO_3)$$

Overflow disposal cost from the returned products queue is assumed as the weighted average of the costs of different quality returned products.

$$CD_2 = (k_1 \times CD_1) + (k_2 \times CD_2) + (k_3 \times CD_3)$$

The system and the cost parameters and values for the model with no classifying are as below:

System Parameters:

z_r	recovery rate for remanufactured product

Cost Parameters:

π_r	expected remanufacturing processing time
ν_r	average rate of remanufactured products
NDO_r	average rate of operational disposals from the remanufacturing process
NQ_j	expected number in the j^{th} queue where $j = 1, 2, 3, 4$
ND_j	average rate of overflow disposals from buffer j where $j = 1, 2$

Cost Values:

CP_r	remanufacturing cost per time
CDO_r	operational disposal cost per unit
CH_j	holding cost per unit/time for the number in the j^{th} queue where $j = 1, 2, 3, 4$
CD_j	overflow disposal cost per unit for overflows from buffer j where $j = 1, 2$

Control Variables:

K_j	Buffer capacity for buffer j where $j = 1, 2$
K_j	Blocking limit for buffer j where $j = 3$
K	Blocking limit for FPS
B	Backorder capacity

Objective Function:

$$\begin{aligned} TC &= (C_{RW} \times RW) + (C_R \times R) \\ &+ (CP_r \times \pi_r \times \nu_r) + (CP_m \times \pi_m \times \nu_m) \\ &+ (CP_a \times \pi_a \times \nu_a) + (CDO_r \times NDO_r) \\ &+ \sum_{j=1}^{2} (CD_j \times ND_j) \\ &+ \sum_{j=1}^{4} (CH_j \times NQ_j) + (CH_{fps} \times NQ_{fps}) + (C_b \times N_b) \\ &+ (C_{ls} \times N_{ls}) \end{aligned}$$

6.1. Comparison of Models

In the comparison of the model with classification and the model with no classification we used four different cost scenarios. In the first cost scenario we used increasing remanufacturing processing costs inversely related to the quality levels of returned products and increasing disposal costs linearly increasing with quality levels. The difference of the cost values (remanufacturing costs and disposal costs) is 2/3 of the mid value, (Table 6.1).

Table 6.1. Cost values (scenario-1)

Cost Values (scenario-1)			
C_{RW}	0.1	CD_1	-0.1
C_R	1	CD_2	5
CP_m	10	CD_3	3
CP_{r_1}	1	CD_4	1
CP_{r_2}	3	C_{ls}	50
CP_{r_3}	5	h	0.01
CP_a	5	α	0.05
CDO_1	5		
CDO_2	3		
CDO_3	1		

By using the cost scenario-1 we simulated 12 experiments with the parameters seen in Table 6.2 for models with classification and with no classification and observed the per cent cost savings (100*((TC(with no class)-TC(with class))/TC(with class)) obtained by classifying returned products according to their quality levels.

While comparing the TC values of the models with classification and with no classification we used the confidence interval approach to a paired comparison in order to test the significance of the difference between TC values obtained by different models. We used maximum half-width levels provided from the simulation results in this approach. According to confidence interval approach to a paired comparison, the confidence interval of the difference between TC with clasification and TC with no classification must not cover a zero value. If this interval covers a zero value then we

Table 6.2. Simulated experiments

Ex	λ	γ	r	k_1	k_2	k_3	z_1	z_2	z_3	f	ω
1	1	0.95	0.8	0.8	0.1	0.1	0.9	0.6	0.3	2	2
2	1	0.95	0.8	0.1	0.8	0.1	0.9	0.6	0.3	2	2
3	1	0.95	0.8	0.1	0.1	0.8	0.9	0.6	0.3	2	2
4	1	0.95	0.8	0.5	0.3	0.2	0.9	0.6	0.3	2	2
5	1	0.95	0.8	0.2	0.3	0.5	0.9	0.6	0.3	2	2
6	1	0.95	0.8	0.333	0.333	0.333	0.9	0.6	0.3	2	2
7	1	0.95	0.8	0.8	0.1	0.1	0.9	0.7	0.5	2	2
8	1	0.95	0.8	0.1	0.8	0.1	0.9	0.7	0.5	2	2
9	1	0.95	0.8	0.1	0.1	0.8	0.9	0.7	0.5	2	2
10	1	0.95	0.8	0.5	0.3	0.2	0.9	0.7	0.5	2	2
11	1	0.95	0.8	0.2	0.3	0.5	0.9	0.7	0.5	2	2
12	1	0.95	0.8	0.333	0.333	0.333	0.9	0.7	0.5	2	2

can not say these two TC values are significantly different, [36].

From the simulation results we observe that maximum half-width for models with the first cost scenario is 0.75. According to this half-width level we analyzed the significant per cent cost savings for the chosen experiments, (Table 6.3).

OptQuest results shows that among the chosen 12 experiments maximum per cent cost saving achieved by using the first cost scenario is 8,934 and the average per cent cost saving is 2,531. We observed from the simulation results that the maximum cost savings by classifying returned products according to quality levels is achieved in the cases where the proportions of different qualities in the returned products are closer to each other viz. maximum in the k_1=0.33, k_2=0.33, k_3=0.33 case. Hence minimum cost savings attained when the system includes mostly one particular quality dominating the returned product mix. The analysis indicates that in the cases where material recovery rates of remanufactured products from different quality levels are closer to each other (z_1=0.9, z_2=0.7, z_3=0.5) we can obtain less significant cost savings by classifying returned products. On the other hand, when the difference between material recovery rates of returned products increases (z_1=0.9, z_2=0.6 z_3=0.3), more significant per cent cost savings by classifying are observed (Figure 6.2).

Table 6.3. per cent cost savings for scenario-1

Ex	TC(with class)	TC(no class)	diff	min	max	% saving	
1	15.721	15.669	-0.052	-0.802	0.698	-0.331	***
2	21.501	21.737	0.236	-0.514	0.986	1.098	***
3	28.686	28.307	-0.379	-1.129	0.371	-1.321	***
4	18.566	19.140	0.574	-0.176	1.324	3.092	***
5	24.025	25.600	1.575	0.825	2.325	6.556	
6	20.998	22.874	1.876	1.126	2.626	8.934	
7	15.211	15.314	0.103	-0.647	0.853	0.677	***
8	19.492	19.522	0.030	-0.720	0.780	0.154	***
9	25.375	25.039	-0.336	-1.086	0.414	-1.324	***
10	17.892	18.366	0.474	-0.276	1.224	2.649	***
11	22.188	22.897	0.709	-0.041	1.459	3.195	***
12	18.522	19.818	1.296	0.546	2.046	6.997	

*** values are not significant

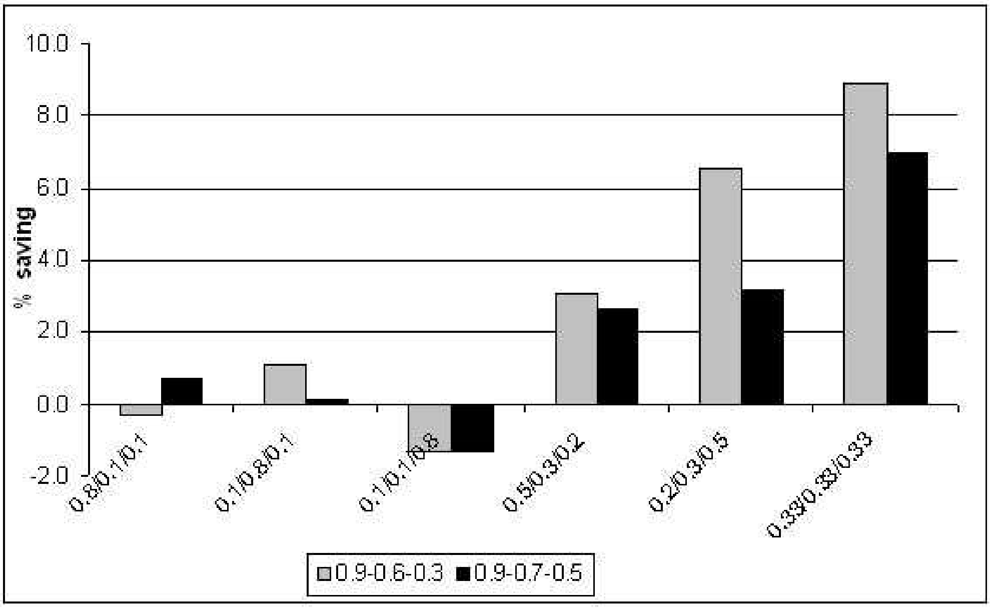

Figure 6.2. per cent cost savings for scenario-1

In the selected 12 experiments we assumed return rate of returned products equals to 0.8. In the following analysis we analyzed the effect of return rate on the per cent cost savings by classifying. We simulated 6 experiments with different return rates, (Table 6.4).

Table 6.4. Simulated experiments

Ex	λ	γ	r	k_1	k_2	k_3	z_1	z_2	z_3	f	ω
1	1	0.95	0.7	0.333	0.333	0.333	0.9	0.6	0.3	2	2
2	1	0.95	0.75	0.333	0.333	0.333	0.9	0.6	0.3	2	2
3	1	0.95	0.8	0.333	0.333	0.333	0.9	0.6	0.3	2	2
4	1	0.95	0.85	0.333	0.333	0.333	0.9	0.6	0.3	2	2
5	1	0.95	0.9	0.333	0.333	0.333	0.9	0.6	0.3	2	2
6	1	0.95	0.95	0.333	0.333	0.333	0.9	0.6	0.3	2	2

From the simulation results we observed that the increase of return rates increases the effect of classifying returned products according to quality levels (Table 6.5). However in the r=0.95 case there is a decrease in the per cent cost saving and we think the reason of this decrease is the joint effects of holding costs and capacity problems (Figure 6.3).

Table 6.5. Effect of return rate for scenario-1

Ex	TC**(with class)**	TC**(no class)**	**diff**	**min**	**max**	**% saving**	
1	22.955	23.099	0.144	-0.606	0.894	0.627	***
2	21.980	23.223	1.243	0.493	1.993	5.655	
3	20.998	22.874	1.876	1.126	2.626	8.934	
4	20.325	22.432	2.107	1.357	2.857	10.367	
5	19.886	21.997	2.111	1.361	2.861	10.616	
6	19.224	20.999	1.775	1.025	2.525	9.233	

*** values are not significant

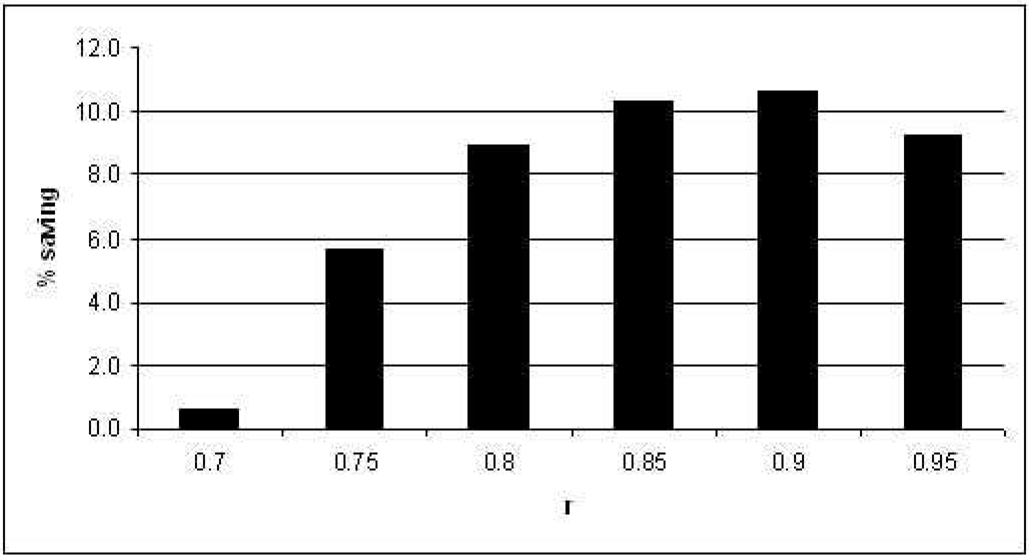

Figure 6.3. Effect of return rate for scenario-1

In the second cost scenario we increased the difference between the remanufacturing cost values of returned products, (Table 6.6). In this scenario we assigned the difference between the remanufacturing costs to 3/4 of the mid value. From the simulation results we observed that maximum half-width for models with the second cost scenario is 0.76.

Table 6.6. Cost values (scenario-2)

Cost Values (scenario-2)			
C_{RW}	0.1	CD_1	-0.1
C_R	1	CD_2	5
CP_m	10	CD_3	3
CP_{r_1}	1	CD_4	1
CP_{r_2}	4	C_{ls}	50
CP_{r_3}	7	h	0.01
CP_a	5	α	0.05
CDO_1	5		
CDO_2	3		
CDO_3	1		

In the third cost scenario we assigned equal remanufacturing costs and disposal costs to different quality typed returned products, (Table 6.7). From the simulation results we observed that maximum half-width for models with the third cost scenario is 0.73.

Table 6.7. Cost values (scenario-3)

Cost Values (scenario-3)			
C_{RW}	0.1	CD_1	-0.1
C_R	1	CD_2	1
CP_m	10	CD_3	1
CP_{r_1}	1	CD_4	1
CP_{r_2}	1	C_{ls}	50
CP_{r_3}	1	h	0.01
CP_a	5	α	0.05
CDO_1	1		
CDO_2	1		
CDO_3	1		

And in the last cost scenario we increased the difference between the disposal cost values of returned products, (Table 6.8). In this scenario we assigned the difference between the disposal costs to 3/4 of the mid value. From the simulation results we observed that maximum half-width for models with the fourth cost scenario is 0.76.

Table 6.8. Cost values (scenario-4)

Cost Values (scenario-4)			
C_{RW}	0.1	CD_1	-0.1
C_R	1	CD_2	7
CP_m	10	CD_3	4
CP_{r_1}	1	CD_4	1
CP_{r_2}	3	C_{ls}	50
CP_{r_3}	5	h	0.01
CP_a	5	α	0.05
CDO_1	7		
CDO_2	4		
CDO_3	1		

For the cost scenarios 2,3 and 4 we simulated the following experiments in order compare the per cent cost savings obtained by these scenarios, (Table 6.9).

Table 6.9. Simulated experiments

Ex	λ	γ	r	k_1	k_2	k_3	z_1	z_2	z_3	f	ω
1	1	0.95	0.7	0.333	0.333	0.333	0.9	0.6	0.3	2	2
2	1	0.95	0.75	0.333	0.333	0.333	0.9	0.6	0.3	2	2
3	1	0.95	0.8	0.333	0.333	0.333	0.9	0.6	0.3	2	2
4	1	0.95	0.85	0.333	0.333	0.333	0.9	0.6	0.3	2	2
5	1	0.95	0.9	0.333	0.333	0.333	0.9	0.6	0.3	2	2
6	1	0.95	0.95	0.333	0.333	0.333	0.9	0.6	0.3	2	2

Simulation results indicate that when the difference between the remanufacturing costs of different quality returned products increases the effect of classifying also increases. We can see this effect from the results obtained by cost scenario 2 and 4, (Table 6.10 and Table 6.11).

Table 6.10. Effect of return rate for scenario-2

Ex	TC**(with class)**	TC**(no class)**	**diff**	**min**	**max**	**% saving**	
1	23.838	24.087	0.249	-0.511	1.009	1.045	***
2	22.777	23.962	1.185	0.425	1.945	5.203	
3	21.668	23.643	1.975	1.215	2.735	9.115	
4	21.021	23.297	2.276	1.516	3.036	10.827	
5	20.295	22.636	2.341	1.581	3.101	11.535	
6	19.956	21.897	1.941	1.181	2.701	9.726	

*** values are not significant

Table 6.11. Effect of return rate for scenario-4

Ex	TC(with class)	TC(no class)	diff	min	max	% saving	
1	23.531	23.990	0.459	-0.301	1.219	1.951	***
2	22.748	23.758	1.010	0.250	1.770	4.440	
3	21.537	23.494	1.957	1.197	2.717	9.087	
4	21.341	23.577	2.236	1.476	2.996	10.477	
5	20.413	22.726	2.313	1.553	3.073	11.331	
6	19.758	21.656	1.898	1.138	2.658	9.606	

*** values are not significant

We observe from the simulation results of scenario-1 that when we assign equal remanufacturing processing costs and equal disposal costs to different quality returned products, we can not achieve any significant cost saving by classifying returned products, (Table 6.12). In such situations we should not classify returned products.

Table 6.12. Effect of return rate for scenario-3

Ex	TC(with class)	TC(no class)	diff	min	max	% saving	
1	21.107	21.168	0.061	-0.669	0.791	0.289	***
2	20.600	20.788	0.188	-0.542	0.918	0.913	***
3	19.496	19.767	0.271	-0.459	1.001	1.390	***
4	18.716	19.160	0.444	-0.286	1.174	2.372	***
5	18.230	18.769	0.539	-0.191	1.269	2.957	***
6	17.765	18.169	0.404	-0.326	1.134	2.274	***

*** values are not significant

Comparison of models with different cost scenarios indicate that classifying returned products according to their quality levels brings significant cost savings when there is difference between remanufacturing processing costs, operational disposal costs and overflow disposal costs of different quality returned products, (Figure 6.4).

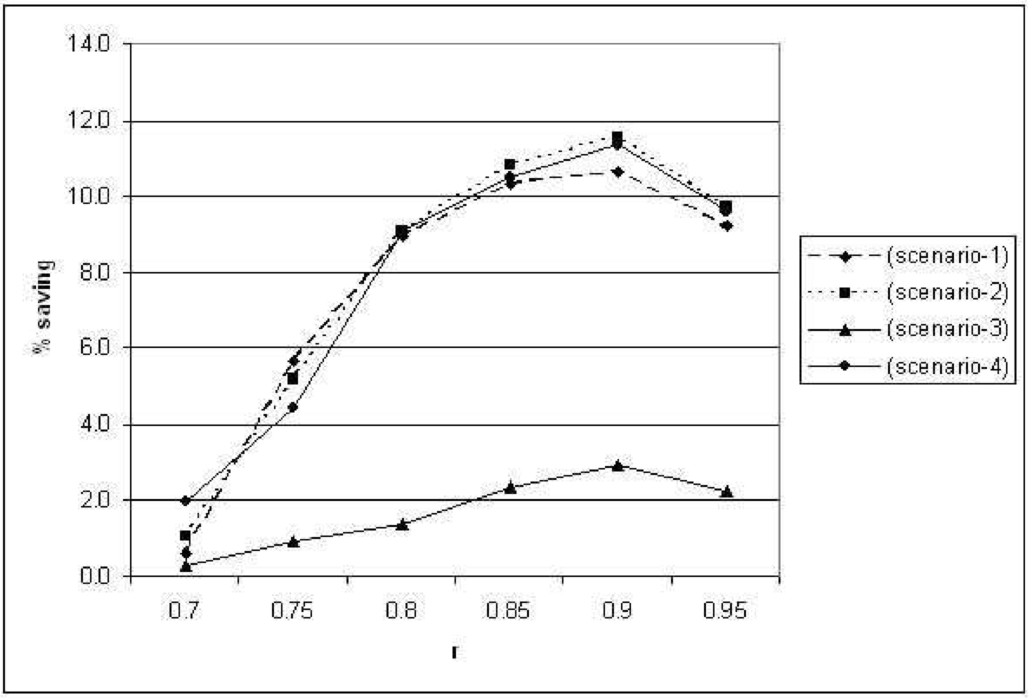

Figure 6.4. Comparison of cost scenarios

In the analysis we do not assign a cost value for classification of returned products. If we make a sensitivity analysis on this cost value, unit classification cost of returned products (C_{class}) must be lower than the difference of the total costs for the models with and without classification. Thus we can say classification of returned products is profitable, when

$$C_{class} \times r\gamma < TC_{noclass} - TC_{withclass}$$
$$C_{class} < \frac{TC_{noclass} - TC_{withclass}}{r\gamma}$$

where C_{class} is the unit cost of classifying a returned product.

We analyze the system profitability with classification cost by using experiment set shown in Table 6.9 and cost scenario-2, Table 6.13.

Table 6.13. Classification cost analysis

Ex	r	γ	TC**(no class)**	TC**(with class)**	**diff**	$C_{class} <$
1	0.7	0.95	24.087	23.838	0.249	0.374
2	0.75	0.95	23.962	22.777	1.185	1.663
3	0.8	0.95	23.643	21.668	1.975	2.599
4	0.85	0.95	23.297	21.021	2.276	2.819
5	0.9	0.95	22.636	20.295	2.341	2.738
6	0.95	0.95	21.897	19.956	1.941	2.151

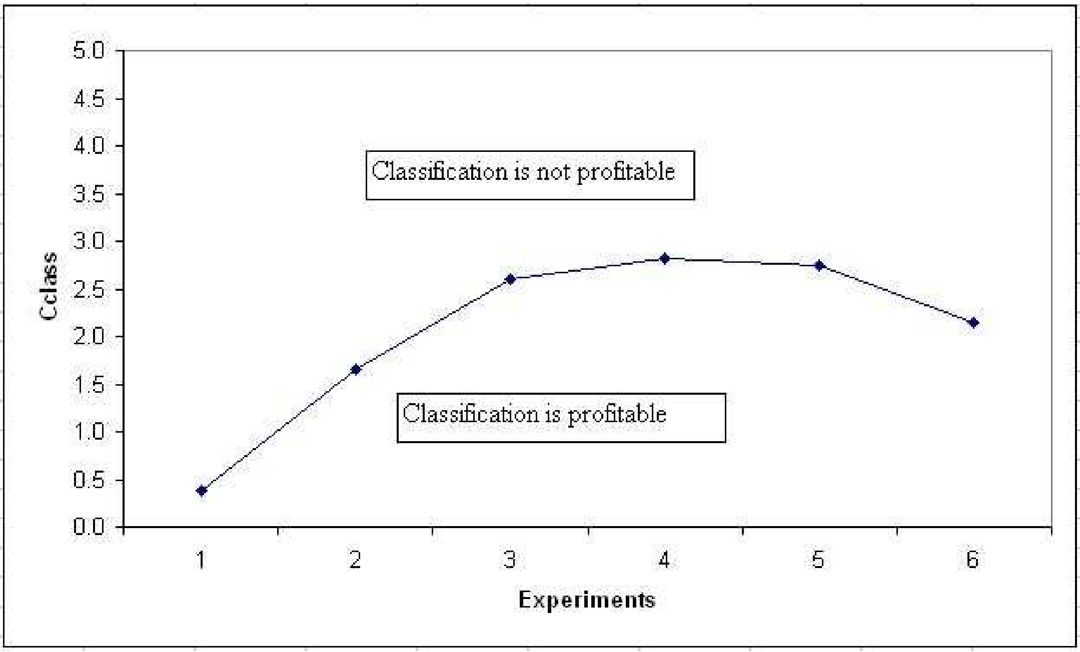

Figure 6.5. Classification cost analysis

6.2. Extension to General Distribution

In this section we analyze the impact of classifying by using general distributed remanufacturing processing times. We used lognormal distribution in our analysis and study different standard deviations as in Section 5.3. In the model with classifying we use the same calculations as in Section 5.3 for the remanufacturing processing times and standard deviations. For the model with no classifying the processing time of remanufacturing operation is calculated as the weighted average of the processing times of different quality returned products.

$$\pi_r = (k_1 \times \pi_{r_1}) + (k_2 \times \pi_{r_2}) + (k_3 \times \pi_{r_3})$$

And the standard deviation of the remanufacturing operation is calculated as follows:

Standard deviation of remanufacturing operation =

$$\sqrt{(c * \pi_{r_1})^2 + (c * \pi_{r_2})^2 + (c * \pi_{r_3})^2}$$

In these comparisons we use three different levels for multiplier c which are 0.5, 1 and 2, and simulate the model with classification and the model with no classification using these distributions. For the analysis we simulate 12 experiments given in Table 6.14 for the cost scenario-1, (Table 6.1).

Table 6.14. Simulated experiments

Ex	λ	γ	r	k_1	k_2	k_3	z_1	z_2	z_3	f	ω
1	1	0.95	0.8	0.8	0.1	0.1	0.9	0.6	0.3	2	2
2	1	0.95	0.8	0.1	0.8	0.1	0.9	0.6	0.3	2	2
3	1	0.95	0.8	0.1	0.1	0.8	0.9	0.6	0.3	2	2
4	1	0.95	0.8	0.5	0.3	0.2	0.9	0.6	0.3	2	2
5	1	0.95	0.8	0.2	0.3	0.5	0.9	0.6	0.3	2	2
6	1	0.95	0.8	0.333	0.333	0.333	0.9	0.6	0.3	2	2
7	1	0.95	0.8	0.8	0.1	0.1	0.9	0.7	0.5	2	2
8	1	0.95	0.8	0.1	0.8	0.1	0.9	0.7	0.5	2	2
9	1	0.95	0.8	0.1	0.1	0.8	0.9	0.7	0.5	2	2
10	1	0.95	0.8	0.5	0.3	0.2	0.9	0.7	0.5	2	2
11	1	0.95	0.8	0.2	0.3	0.5	0.9	0.7	0.5	2	2
12	1	0.95	0.8	0.333	0.333	0.333	0.9	0.7	0.5	2	2

The simulation results indicate that when c=0.5, the TC values decrease according to exponential models, when c=1, the TC values of exponential cases and lognormal cases get closer and when c=2, the TC values obtained by lognormal cases exceed the exponential cases, (Figure 6.6).

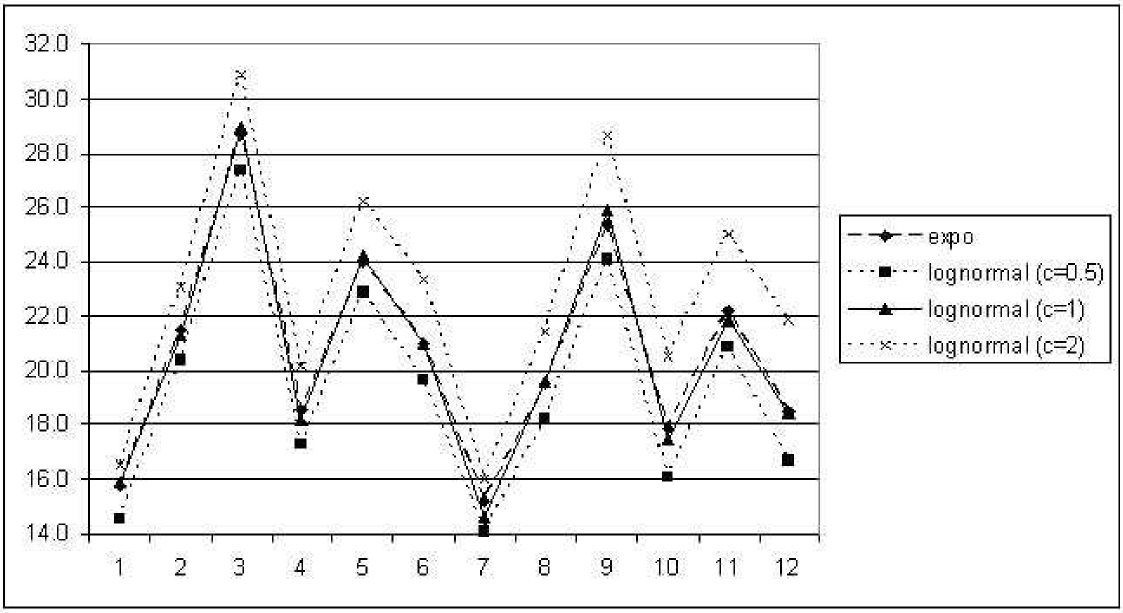

Figure 6.6. per cent differences between exponential and lognormal cases

We simulate the model with no classification for lognormal distributions and analyzed the per cent cost savings from model with classification case. Our analysis indicate that when the variance of the distribution is lower (c=0.5) then the impact of classifying decreases, when c=1 the impact of the classifying approximately the same as the exponential case and when the variance of the distribution is higher (c=2), the impact of classifying increases, (Figure 6.7).

In conclusion we can state that using general distributions for the remanufacturing processing times effects the impact of classifying returned products according to quality levels. If the variance of the used distribution increases then the cost savings by classifying also increases.

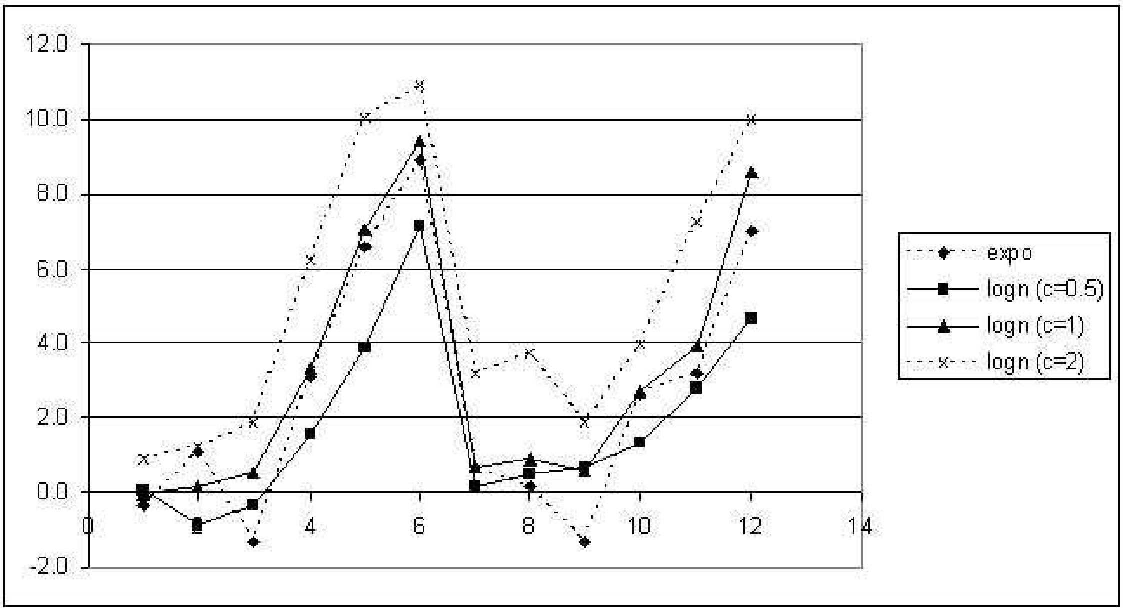

Figure 6.7. per cent cost savings for general distributions

7. CONCLUSION AND FURTHER RESEARCH

Remanufacturing companies face several complicating factors such as uncertainties in the quality, quantity and timing of product return flows. These uncertainties in return flows lead to stochastic routings and production lead times. There are also uncertainties in the remanufacturing processing times and the recovery rate of the process due to different quality levels of return flows. Because of these uncertainties it is hard to balance returns with demands in a hybrid system. Typically remanufacturing operations have shorter processing times and consume less energy and natural resources. However, product return rate is always less than or equal to the demand rate which leads companies to manufacture new products besides remanufactured ones in order to satisfy the total demand.

In this study, we modeled and analyzed a hybrid system including both remanufacturing and manufacturing operations allowing different quality levels for return flows. In the first phase we searched for the inventory control policy that balances the system and minimizes the cost function. Here we constructed a single stage inventory control model in order to achieve an upper bound for our objective function where we analyzed the system using Jackson networks. This model was a base model for our studies which gave us the maximum throughput of the system. By the help of this analytical model we performed a numerical analysis for the effects of system parameters on the cost function. We observed that the most important factor affecting the cost function is the probability of return arrivals (k_i) which showed us the importance of classifying returned products. Experimental analysis indicated that the total expected cost per unit (TC) decreases as the return rate increases. The increase of expected processing time of the manufacturing operation relative to the expected processing time for the remanufacturing process (f) causes an increase on TC. Also as the relative difference of remanufacturing processing times (ω) increases TC decreases in most of the cases. However in the cases where the proportion of bad quality arrivals are greater than others some capacity problems arise for manufacturing and remanufacturing processes. Our suggestion to the system managers is to increase related capacities in these cases or to use capacitated queues to decrease queue lengths.

At the second stage of our analysis we constructed two different multi stage inventory control simulation models which use blocking mechanisms in order to balance the system throughput with demand arrivals. In the first model with blocking we used this blocking mechanism at every stage of the system. This model provided us on the average a 37.705 per cent decrease in the TC for the selected experiments compared with the TC values found in the single stage inventory control model. In this model we observed that the system tends to block manufacturing operation in all experiments instead of remanufacturing. Then we constructed the second model which also uses blocking mechanisms. In this model we used blocking only for the manufacturing operation. When we analyzed the proposed best TC values of this model, we noticed that there is on the average 38.042 per cent decrease in the TC among the chosen experiments compared with the TC values found in single stage inventory control model. The multi stage inventory control model with blocking manufacturing operation provided the minimum TC values on the average among the other models. Therefore we used this model for the sensitivity analysis in this thesis.

At the construction of models we used exponential distribution for processing times of operations. However, in order to reflect a more realistic hybrid system environment we simulated these three models with using lognormal distributions for the remanufacturing processing times. This way we had the chance of observing the impact of the variance of the distribution on the TC. Our analysis denoted that with smaller variances TC values decrease according to exponential models and when the variance of the distribution increases TC values obtained by lognormal cases also increase. The reason of this effect is increasing queue lenghts of the buffers before the remanufacturing operation by increase of the variance of the distributions for remanufacturing processing times. The decrease of queue lengths decreases the holding costs and thus decreases the total expected cost per unit (TC) and the increase of queue lengths increases the holding costs related with these queues and thus increases the TC.

In the second phase of this thesis we investigated the impact of quality uncetainties of the returned products on the hybrid system. For this purpose we constructed a benchmark model which assumes no classification of returned products, in order to study the impact of classification. We observed the % cost improvements by classifying returned products compared to the not classifying case. Our analysis with different cost scenarios denoted that quality based classifying of returned products brings significant cost savings in the cases when;

- the return rate of returned products is high,
- the arrival rate of different quality returned products is closer to each other,
- the difference between material recovery rates of returned products is high,
- there is difference between remanufacturing processing costs, operational disposal costs and overflow disposal costs of different quality returned products.

By classification of returned products, system can select the product type to produce more and the product type to dispose by using blocking limits and disposal capacities. Certainly in order to minimize the cost function, the system tends to produce the products which have minimum producing costs, while disposing the products which have minimum disposal costs. Classifying returned products gives the opportunity to the hybrid system to produce more of the good quality returned products and to dispose especially bad quality returned products which minimizes the TC. Our numerical analysis indicated that by classifying managers can achieve greater than 8 per cent cost improvements at the higher return rates.

Finally we simulated models with clasification and with no classification by using lognormal distributed remanufacturing processing times under different variances, where we observed that using general distributions for the remanufacturing processing times effects the impact of classifying returned products according to quality levels. If the variance of the used distribution increases then the cost savings by classifying also increases.

In this thesis we constructed an analitical model for single stage inventory control case and used simulation for other cases. This study can be extended by analyzing multi stage inventory control models using queueing networks. In addition we classified returned products into three quality levels and observed significant cost savings due to this classification. Classifying returned products into more quality levels can bring extra cost savings since the more we classify the more we decrease the system variance.

APPENDIX A: BEST VALUES FOR THE CONTROL VARIABLES

This appendix includes the tables (Table A.1 and Table A.2) representing the provided control variables for Model-2 and Model-3 by OptQuest for the best TC values.

Table A.1. Best values for the control variables of Model-2

Ex.	$K1$	$K2$	$K3$	$K4$	$K5$	$K6$	$K7$	$K8$	K	B
1	20	23	10	12	1	15	8	14	4	5
2	29	25	10	28	1	22	7	27	5	6
3	2	11	12	5	1	11	1	18	1	9
4	30	4	30	11	1	30	30	1	5	3
5	3	7	6	2	1	6	1	8	4	6
6	26	11	4	12	1	6	25	17	3	4
7	30	15	30	14	1	30	27	1	6	1
8	23	6	24	4	1	20	25	5	5	3
9	15	6	22	8	1	15	23	9	5	4
10	30	4	20	15	1	21	23	13	9	6
11	23	12	25	13	1	24	21	6	4	3
12	1	14	30	4	1	30	30	30	6	1
13	30	10	28	7	1	29	29	6	7	2
14	26	4	30	6	1	30	30	12	6	1
15	18	13	13	8	1	10	15	10	9	2
16	17	8	13	6	1	16	10	6	4	3
17	10	30	30	30	1	1	26	22	3	9
18	1	30	1	12	1	30	30	1	2	9
19	13	9	7	7	1	11	7	16	3	6
20	11	12	8	12	1	9	1	1	4	7
21	3	6	6	6	1	6	6	6	3	6
22	9	5	14	3	1	4	1	16	4	4
23	14	6	21	4	1	16	15	10	3	5
24	7	1	30	24	1	29	29	5	3	4
25	14	3	3	4	1	7	30	22	7	3
26	19	17	27	17	1	1	30	26	4	7
27	30	12	30	26	1	30	18	26	4	4
28	14	14	7	9	1	8	17	8	9	4
29	29	17	29	11	1	21	24	10	4	4
30	12	4	6	11	1	11	15	6	6	5

Table A.2. Best values for the control variables of Model-3

Ex.	$K1$	$K2$	$K3$	$K4$	$K5$	K	B
1	5	7	3	1	1	3	5
2	6	4	4	3	1	4	6
3	8	11	8	6	1	3	10
4	7	5	5	4	1	3	3
5	21	20	23	17	1	4	6
6	4	9	8	3	1	2	6
7	6	3	3	1	1	5	1
8	9	6	19	15	1	5	5
9	13	9	16	9	1	2	6
10	13	16	14	5	2	5	3
11	14	10	9	5	2	5	5
12	15	7	17	9	1	4	3
13	15	9	7	6	3	4	4
14	7	19	6	4	4	4	3
15	11	16	7	8	3	6	3
16	15	17	18	5	1	3	6
17	8	19	27	12	1	3	5
18	4	11	11	3	1	4	8
19	4	9	6	2	1	5	3
20	16	5	30	7	1	5	6
21	5	9	7	3	1	4	8
22	4	5	9	3	3	1	5
23	11	9	11	4	1	4	4
24	9	9	14	13	1	2	8
25	12	30	14	8	1	4	1
26	9	5	8	6	2	3	6
27	4	8	16	8	1	2	5
28	10	5	5	15	1	5	4
29	4	6	5	8	1	4	3
30	6	6	7	16	1	4	5

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