A DECISION SUPPORT SYSTEM
FOR INVENTORY MANAGEMENT OF
INFORMATION TECHNOLOGY SPARE PARTS

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A DECISION SUPPORT SYSTEM
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DECLARATION OF ORIGINALITY

I, Aycan Turan, certify that

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- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
- this is a true copy of the thesis approved by my advisor and thesis committee at Boğaziçi University, including final revisions required by them.

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ABSTRACT

A Decision Support System for Inventory Management

of Information Technology Spare Parts

Rising operational costs have become a major issue in developing countries, causing many leading information technology (IT) companies to focus on inventory optimization. This thesis research concentrates on inventory policy optimization and decision making process. We develop a decision support system (DSS) that provides an optimal control of IT spare part inventory to minimize the total cost. The system supports a continuous review (Q, r) inventory policy and a periodic review (S, s) inventory policy options for managing the spare parts inventory. The DSS includes a forecast model to estimate the failure rates of different device types purchased in different time periods. It is also enhanced by a simulation environment which evaluates different inventory management scenarios and choses the optimum one. Next, the DSS is applied to a real system and optimum inventory management scenario is determined according to the cost and service performances. Experimental design analysis is performed to measure the sensitivity of optimal total cost with respect to input parameters such as inventory holding cost, part order cost and penalties. The DSS provides an efficient, effective and flexible decision making environment for the optimal control of IT spare parts.

ÖZET

Bilgi Teknolojileri Cihazları için Yedek Parça Enventer Yönetimi Karar Destek Sistemi

Gelişmekte olan ülkelerdeki artan operasyonal giderler nedeniyle bilgi teknolojileri (BT) firmaları operasyonel mükemmeliyet konusuna odaklanmaktadır. Operasyonun temel kısımlarından biri olan yedek parça envanter kontrol politikasının doğru belirlenmesi, maliyet ve servis kalitesi açısından büyük fayda sağlamaktadır. Bu tez çalışması kapsamında BT yedek parça envanter yönetimi konulu bir karar destek sistemi (KDS) geliştirilmiştir. Bu KDS aynı tip yedek parça kullanan BT cihazları için ileriki dönemde beklenen ortalama arızaları tahmin eden bir model içermektedir. Bu modele göre toplam ortalama yedek parça talebi belirlenmektedir. Poission dağılımına göre rastgele arızalar üretildikten sonra, bu arızaların giderilmesi için en düşük maliyetli enventer yönetim senaryosu belirlenmektedir. KDS, envanter depolama maliyeti, parça sipariş maliyeti ve ceza maliyeti içeren bir simulasyon ortamı içermektedir ve yaygın kullanılan (Q, r) ve (S, s) envanter politikalarını desteklemektedir. Ayrıca kullanım kolaylığı için grafik arayüz oluşturulmuştur. Bu arayüz üzerinde gerçek bir örnek test edilmiş, maliyet ve performans çıktıları değerlendirilmiştir. Bu çalışma sonucunda mevcut envanter polikası iyileştirilmiş ve operasyonal verimlilik artışı sağlanmıştır. Ayrıca, başlangıç koşullarının toplam maliyete etkisi araştırılmıştır. Bu tez çalışması kapsamında geliştirilen KDS, etkili, verimli ve uyumlu bir karar verme ortamı sunmaktadır.

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ABBREVIATIONS

CDF: Cumulative Distribution Function

CRM: Customer Relationship Management

DSS: Decision Support System

EOQ: Economical Order Quantity

GUI: Graphical User Interface

IDC: International Data Corporation

IMS: Inventory Management Scenario

IS: Information System

IT: Information Technology

MIS: Management Information System

MS : Microsoft

PDF: Probability Distribution Function

RM: Rapid Manufacturing

SLA: Service Level Agreement

VNI: Visual Networking Index

CHAPTER 1

INTRODUCTION

Nowadays, spare part management is a significant issue among international IT companies that have similar maintenance operations in many countries around the world. IT products are monitored by free or paid monitoring services including event logging systems. In case of a hardware failure or proactive action, spare parts are used by technicians. In a general scenario, the failed component must be replaced with the new one as soon as possible. In a 7x24 online environment, IT local support is exposed to some risks such as having too much or too little spare part stock. It is mainly due to uncertain nature of hardware failures. Although inventory holding costs are relatively expensive, it is necessary to stock high quantity of physical spare parts to avoid system outage. On the other hand, if the size of order exceeds current need, it may cause an overstocking problem. Hence, it is essential to estimate failure patterns properly for an efficient inventory optimization.

In a large scale IT environment, failure information of data storage devices is analyzed in order to explore periodic trends. Part demand increases at an increasing rate at initial quarter periods. For the rest of product life cycle, part demand increases at a decreasing rate and it starts to converge at a constant level after several years of operation. Considering the failure trends, it is necessary to provide an accurate forecast model for part failures in order to estimate their future demand. Several forecast models are compared and the most fitting one is chosen to model same kind of deteriorating failures.

It is also required to simulate cost and efficiency performance by using random failures according to the model while optimizing inventory policy of maintenance service. From maintenance service point of view, there are many devices purchased in different time periods and all of them are under warranty within three years of operation. Since the operational age of each device is different from each other, individual demand must be estimated according to the forecast model. Total spare part demand must be calculated by adding independent demands of several devices for each time period. In addition, device types can be different and it must be taken into account while analyzing failure trends. Types can have different failure patterns that results in different forecast models to estimate mean demand rate for any time period. The problem becomes even more complex for service companies due to actual fluctuations around the estimated mean demand rate.

Generally, IT maintenance companies have upper level contract options that include high amount of penalty charges in case of stock-outs. Customers accept high payments to the maintenance company for high level service in order to ensure that all critical applications and services are up and running in 7x24 basis. For such cases, it is necessary to provide high quality datacenter maintenance services to protect running applications from environmental errors. When we make effect analysis on the environment, it is said that some devices are definitely more important. One of the most important devices in datacenter environment is the data storage device. It stores data which is one of the most important assets of customer. For example, in case of a system failure, operating system can be reloaded from any other source, however it is not possible to restore company data such as invoices, customer records and other important business transactions unless the data is backed up. It clearly shows high importance level of the data compared with other components of IT environment.

Since the data is unique and even secret for corporations, storage optimization and disaster recovery solutions have become more important and more expensive gradually. For large scale customers such as telecom operators and banks, availability is an obligatory feature considering critical applications like customer relationship management (CRM) and billing applications. These applications have wide range of usage from delivering end-customer experience to managing resources. In case of a system outage, end customer experience have a massive negative effect. In order to eliminate such risks, IT maintenance companies have to provide service immediately in case of a storage device part failure. That is why local technical support companies have to keep spare parts available all time.

There are several issues related to part availability. Most of the time, these parts are shipped from Far East countries and order lead time is approximately one month. In case of simultaneous failures, stock out problem may occur due to long shipping duration. For such cases, fast courier transport option can be used although it is more costly compared to regular shipment orders. Another part availability issue is the customs tax. This tax is relatively high for the critical spare parts. Due to the long order lead time and high ordering costs resulting from high taxes, parts are ordered in large quantities. Although large order quantities may lead to discount advantages in the unit purchase price, this obviously results in high inventory levels and high part holding costs from maintenance company perspective.

In the macro level, Gallagher (2005) states that total revenue of service part industry became $200 billion worldwide. Many leading service companies obtain up to 40% of profits from their aftersales services. Moreover, operational and managerial efficiency of aftersales business can increase company profits up to 25 percent. Since pricing and low growth rate are common dreadful factors resulting in decreased revenues, it is indicated that business mostly focus on decreasing operational expenses by optimizing inventory related costs. Therefore, additional value can be generated for stakeholders and potential financiers. Choosing the best inventory management policy is one of the most effective subjects to decrease operational costs. Eaves and Kingsman (2004) assert that small revisions in spare parts management area may lead to considerable cost savings. It is also stated that real data must be used and various forecasting methods must be compared before modelling the inventory policies.

According to the forecast of Cisco Visual Networking Index (2013), annual global IP traffic will surpass the zettabyte threshold (1.4 zettabytes) by the end of 2017. In addition, it is said that IP traffic is growing the fastest in the Middle East and Africa. Moreover, IDC (2014) indicates that total digital data size will grow by a factor of 10 (from 4.4 trillion to 44 trillion gigabytes) from 2013 to 2020. It is also argued that emerging markets will surpass mature markets by 2017 and 60 percent of the data in the digital universe will be generated by emerging markets in 2010.

It clearly shows that enormous data storage capacity will be demanded in near future. Considering the exponential growth in data size, IT investments and related demands for IT spare parts will substantially increase. Rising IT part holding expense causes huge increment on total maintenance cost. Thus, better management of the spare parts inventory will be even more critical in near future. In addition, inventory policy must be updated as it is not as effective as planned at initial step.

With this motivation in this thesis study, first a forecast model is developed to estimate the mean demand of IT spare parts. The model is applied and validated on a real data obtained from an IT maintenance company. These forecasts are used in simulation model to generate optimal inventory control policies based on (Q, r) and (S, s) inventory control strategies. Next, the DSS is developed in order to provide an optimal control of IT spare part inventory for multiple device operations. The generated DSS provides an efficient, effective and flexible decision making environment by performing experimental design and supporting scenario analysis.

The organization of the thesis is as follows: In the next section, we provide a literature survey of the studies in the spare parts inventory management area. Then, failure forecast methodology and inventory models are explained in detail. As a next step, decision support system algorithm and modular parts of the system are discussed. Finally, experimental design is performed and sample scenarios are simulated in the DSS. Results and future work are provided at the end.

CHAPTER 2

LITERATURE REVIEW

Spare part optimization and inventory management studies are examined by several authors as an independent research area (Mentzer, 2001) (Gibson, 2005) (Christopher, 2005). Gallagher et al. (2005) state that customers purchase new products in every couple of years, however spare parts are purchased throughout the product life cycle in case of a failure. Sales of spare parts is defined as a continuous income resource for original equipment providers after completing sales process. As a result, Vigoroso (2005) points out that leading companies focus on improving aftersales and technical support service more than product manufacturing.

Noeuveglise and Chevenement (2011) state that spare parts business can provide up to 50% of net profit for industrial companies. It is mainly preferable due to high profit rates. In addition, Cohen et al. (2006) asserts that 10% of sales revenue is a result of aftermarket business that combines spare part sales and maintenance service. It is also claimed that there is strong connection between new product purchase and aftersales service. For instance, customers are willing to buy same brand equipment if technical support and spare part service is satisfactory enough. However, many companies do not have much attention on aftersales service, as they do not obtain regular income due to uncertain demand. Braglia (2004) and Vigoroso (2005) highlights that spare part sales is difficult to forecast, since it is only needed when a breakdown occurs. Likewise, there are several challenges such as increased inventory holding costs due to low turnover rate. Hence, it is vital to investigate inventory control policies described in the literature.

2. 1 Inventory control policies

Two main inventory control systems which named continuous review and periodic review systems are commonly used to manage spare part inventories. Continuous review model provides two parameters that refers to reorder level and order size. Dhakar (1994) examined base stock level determination for expensive critical spare parts under low demand conditions. Expedite delivery is developed for some important parts and orders depending on the level of urgency. Chiang (2002) updated the model with threshold time parameter which accelerates critical orders under certain circumstances. When manufacturing time is constant, system decide whether emergency delivery is required. It decreases time of shipping by fastening order processes. Dohi (2009) also improved the model for orders not delivered in time. In case of unexpected latency, a new emergency order is placed and current order is cancelled. It is considered useful if shipping service supports emergency option. Since delivery cancel process depends on certain conditions, cancelation penalty may be charged without customer permission.

Ravindran and Warsing (2012) state that an alternative to continuous review approach is periodic review methodology. When we compare performance of both methods, it is said that periodic review performance is relatively lower as it requires more parts to guarantee service levels. Periodic review methodology is generally preferred for midrange material demand in order to decrease monitoring costs. Although it is indicated that (S, s) periodic review policy is optimal for fixed order cost scenarios, penalty cost must be taken into account as periodic inventory check decreases overall inventory performance. Since penalty costs are much higher in especially information technology sector, safer solutions are generally recommended by advisors.

Recent works on inventory management show an improved version of base stock policy that uses two order-up-to levels. It is argued that defining a lower order up-to level decreases total costs. Dual Index base stock policy is suggested by Veeraraghavan et al. (2008). When inventory level is below the lower limit, an emergency order is placed. Next, regular orders are placed gradually to increase number of spare parts to higher order up-to level (Allon, 2009) (Sheopuri, 2010) (Zhou, 2011). In like manner, Amaruchkul (2012) improved total cost optimization by using periodic review model. Transaction probability is calculated for each of pre-defined scenarios. Moreover, Ozsen (2012) improved periodic review inventory system that uses expediting policy in many settings. As the unit expediting cost is less than backorder penalty, it is recommended to place fast type order in case of emergency. Although inventory responsible cannot control lead time and delay, shipping severity can be identified to speed up process. Expediting order option makes periodic review base-stock policy more optimal. Optimizing inventory is one of the most critical improvement areas that we discussed in next chapter.

In order to optimize inventory, it is necessary to consider the issues related to transportation media, lot size and importance level. According to Christopher (2002), part orders are classified based on demand, lead time and product type. He adds that an advantageous policy for standard products is preferring overseas manufacturers if demand is predictable. Besides, domestic manufacturers are more suitable when unstable demand exists for special products. In case of unexpected demand, a third alternative order method must be designed for timely response. As a reason, maintenance industry requires shorter response time for critical spare part supply such as next business day delivery (Cohen et al., 2006).

Rapid manufacturing (RM) provides quicker response compared to other approaches as production depends heavily on part orders. Holmström (2010) concentrates on RM in spare parts supply chain. The main goal is to increase productivity by optimizing inventory costs under inadequate demand. He also adds that there are several concepts such as distributed and centralized production. For instance, centralized inventory reduces the demand of safety stock and raises turnover rate. In addition to lower inventory, it provides simpler supply chain and shorter lead time. Rapid manufacturing becomes more suitable if alternative transport options are available and inventory holding cost is relatively high.

Boone (2008) examines critical challenges of service part inventory management. He points out that uncertain demand is one of the biggest challenges considering high inventory costs. For such cases, backorder might be an option if customer environment tolerates simultaneous failures. According to Sobel and Zhang (2001), backorder strategy improves overall efficiency of inventory. The deterministic demand is met without delay, but stochastic demand can be backordered. When demand is prioritized, it is easier to determine order size and type. Although backorder policy is not allowed for data center environment due to risk of system downtime, it can be an option for customers who have base-level support contract.

Kranenburg (2004) states that defining critical level policy for each service level is extremely important considering customer differences. After determining maximum waiting time, it is recommended to assign customers and devices to the service groups. He also adds that maintenance companies must provide minimum downtime with respect to priorities of customer. For example, banks are more sensitive to application availability when compared to insurance companies. In case of an access problem, insurance clients can postpone information retrieval for a while. When data becomes available, the information can be requested again. On the other hand, unavailability means revenue loss from bank perspective. Therefore, service level agreements (SLA) must be defined clearly including after sales service commitment such as responsibilities and penalties. All parties must be agreed on SLAs as it is formal contract.

On the other hand, there are some challenges that make inventory management harder and more complex. For instance, different model spare parts must be stored simultaneously, although some of them are not used for months. Moreover, infrequent demand causes inventory size to be increased unnecessarily. Eaves and Kingsman (2004) state that slower demand parts compose more than half of total inventory cost. In order to analyze efficiently, spare parts must be classified into several groups according to turnover rate and period. It is proposed that practical usage of forecasting methods must be compared considering this classification. Similarly, Zokaei and Hines (2007) examine two-dimensional supply chain framework where spare parts and products are disaggregated into groups according to their importance levels. The framework provides more effective IT supply chain by framing activities into categories regarding product life cycle.

Sleptchenko (2005) investigates the scheduling of spare parts and analyzes the effect of priorities in spare part repair process. He indicates that repair shop throughput time is a key parameter regarding stock levels of repairable items. In his study, system failures occur according to Poisson process, a discrete probability distribution. Also, item faults cause system failures which is similar to our work. Different from our work, he models the repair process of failed parts rather than replacing them with new ones. However in our case, even short application service outage may cause mass negative impact on company income and brand image. In order to decrease the risk of service downtime, failure distributions are investigated in detail. Turan et al. (2014) indicates that failure rates of information technology hardware products can be predicted accurately considering first two-year operational disk drive failures. The longer a hardware component is in use, it is more likely to fail. Weibull distribution is commonly used to model that kind of deteriorating failure.

Fewer research emphasizes the improvement of effectiveness by focusing on company image and customer satisfaction (Zokaei and Simons, 2006). For instance, Toyota has improved supply chain techniques to deliver maximum value to customers. Moreover, it is claimed that primary strategy of Toyota Production is focused on consumer satisfaction and service levels more than decreasing service costs (Rich, 1999). In addition, EMC presents customer service as an investment for future sales. Return of investment is measured according to customer satisfaction and retention ratios (Goldstein, 2002). It confirms that the largest technology and industry companies are also figured out the importance of aftersales service.

2.2 Decision support system

Due to the variety of articles related to inventory management and optimization, a decision making tool might be required to identify optimal inventory policy combination. The DSS provides valuable information to evaluate how inventory policies, models and parameters affect the inventory levels according to preferred inventory control policy in terms of service level and costs. Since any improvement on inventory policy makes the operation more efficient, the DSS can lead to quite high savings considering the positive effect on efficiency and effectiveness.

The DSS for inventory management and control subject is studied by several authors. Achabal (2000) investigates inventory management modules of a Vendor Managed Inventory DSS which includes a manufacturer and its retail partners. Weekly forecasts are performed at product level by using forecast model of the DSS. The forecast model parameters are estimated by linear regression at first. It compares R-square values of different combinations according to trial and error. Final form is developed separately for each retailer. The DSS provides performance measures such as inventory turnover rate and customer service level.

In addition, Shang et al. (2008) designs a DSS for a large pharmaceutical company which has 51 brand groups and $100 million annual sales. Existing ordering system is similar to periodic review inventory control policy with a constant order-up-to level (S). It is improved by adding safety stock due to stochastic demand. Historical error data is provided by company planning department and it is used to simulate monthly demand. In this thesis, stochastic demand and dynamic order up-to level are similar, however it is necessary to model demand for each IT device as the forecast is not provided by the IT Service Company.

Next, Uribe (2011) provides a framework for DSS for inventory management area. ABC classification is used to assign priorities for various part types. Constant lead time is similar, however, inventory model is different compared to this thesis. It is said that Economic Order Quantity model can be used to determine order size. In the existence of fixed ordering and storage costs, they develop an EOQ based inventory control policy which is not suitable for us, as the demand for IT spare parts fluctuates quarterly. This thesis examines optimum inventory policy by minimizing total cost and increasing service level.

CHAPTER 3

METHODOLOGY

Firstly, we investigated distribution models to estimate mean demand of IT spare parts. Then, a failure forecast model is generated by using weibull distribution as suggested in the literature, and tested by weibull curve fitting algorithm of MATLAB tool on a quarterly data obtained from a maintenance service company. Next, the weibull model is validated by a simulation model that generates failures where the mean periodical failure rate is obtained by weibull estimation and the periodical failures follow a nonstationary Poisson process. Next, the simulation model is extended to observe the cost and service level performances of inventory control policies based on (Q, r) and (S, s) strategies. As a next step, the simulation environment is used to optimize the order quantity and reorder level decisions. Finally, simulation models are embedded into a DSS by the addition of a graphical user interface (GUI) to be used by inventory control managers in an efficient, effective and flexible decision making environment. The DSS provides the optimal control of IT spare part inventory used in devices with different ages and that are subject to random failures. Lastly, the DSS is used to observe the effects of parameter changes on the optimal decisions by experimental design and scenario analysis.

CHAPTER 4

DEVELOPMENT OF INVENTORY CONTROL MODELS

This section contains problem definition, failure rate estimation model and inventory control model details. Firstly, we provide the IT spare part inventory control problem. In order to drive optimal control policies for inventory management, it is necessary to define demand structure for the IT spare part. Hence, secondly IT device failure rate estimation models are explained where a function of Weibull distribution is used to estimate the mean number of failures in a quarterly period. Actual failure data is considered as an input for determining the coefficients of the estimation model. Next the estimation model is validated by generating random failures for each quarter. The number of failures in a quarter is assumed to be Poisson distributed where the mean failure rate in a quarter is obtained from the estimation model. Next, validation is performed by comparing actual average failure rates with the simulated failure rates. In the third part, two inventory control models, i.e., (Q, r) and (S, s) policies are suggested and explained in detail.

4.1 Problem definition

In this thesis, we consider the IT spare parts inventory control problem of a maintenance service company. The maintenance service company serves several customer companies each having multiple IT devices. These IT devices are of two types and use the same IT spare part. IT devices are subject to random part failures where the mean failure rate increases with the age of the device. When there is a failure, the spare part is replaced by the maintenance service company with a new one from the inventory with no cost due to the service contract made by the customer.

The maintenance service company applies an inventory control policy to replenish the stocks when the stock level decreases to a reorder level. A unit storage cost, c = 90 USD/unit/quarter is charged for every IT spare part that stays in the inventory for one quarter. A regular ordering cost, $w = 500$ USD/order, which is independent of the amount of order is charged when a regular order is placed, i.e., $Q>0$. Orders are delivered after an order lead time l = 30 days. If a stock out occurs during order lead time, then an emergency delivery order is placed for only one IT spare part to avoid system down risk of the IT device of the customer. This incurs a high emergency ordering cost, $p = 5000$ USD/stock-out.

The performance of the inventory control policy is evaluated in terms of the total cost associated and the service level performances. The total cost TC_t in quarter t is the sum of inventory holding cost, ordering cost and penalty cost in quarter t. Let X_t be the on hand inventory level in quarter t. The total cost in quarter t, TC_t is formulated as:

$$TC_t = cX_t + pM_t + wN_t \tag{1}$$

where M_t and N_t are the number of emergency orders and number of regular orders in quarter t respectively. The service level SL_t performance is measured in terms of the percentage of on time replacements in quarter t. Letting total number of failures occurred in quarter t, K_t the service level SL_t is formulated as:

$$SL_t = (1 - \frac{M_t}{K_t}) \times 100 \tag{2}$$

4.2 Mean failure rate estimation models

In this section, models are developed to estimate the quarterly failure rates of two types of IT devices. First, weibull distribution is proposed to estimate the mean quarterly failure rates, and then Poisson distribution is used to predict the number of failures in each quarter. The mean failure rate estimation model is based on weibull distribution as suggested in the literature and explained in previous section. Versatile structure of the distribution leads to better interpretations. For instance, changing failure rates can be modeled by using functions of weibull probability distribution. When the parameters are properly chosen, the function can be adjusted for increasing failure rate, decreasing failure rate or constant failure rate. The Weibull probability density function is as follows for discrete random variable $t \geq 0$;

$$f(t, \alpha, \beta) = \frac{\alpha}{\beta}\left(\frac{t}{\beta}\right)^{\alpha-1} e^{-\left(\frac{t}{\beta}\right)^{\alpha}} \tag{3}$$

Here, alpha (α) is the shape; beta (β) is the scale parameter. Figure 1 shows the change in the PDF with respect to the choice of different shape parameters.

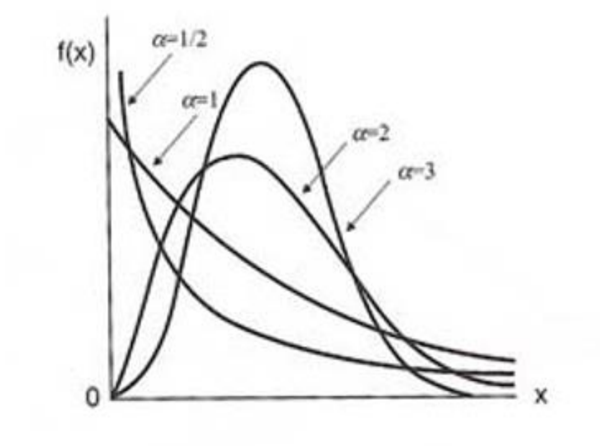

Fig. 1. PDF for Weibull distributions

The Weibull cumulative distribution function (CDF) is as follows for the discrete random variable $t \geq 0$;

$$F(t, \alpha, \beta) = 1 - e^{-\left(\frac{t}{\beta}\right)^{\alpha}} \tag{4}$$

In our actual system, there are two types of IT devices using the same spare part product. The actual data includes the quarterly failure rates of 7 IT devices collected quarterly in

3 years. 4 of these IT devices are of type 1 and rest of them are type 2. Given actual data for the quarterly average failure rates of IT devices of a specific type, the mean failure rates can be estimated by using a function of the CDF of Weibull distribution according to the equation 5.

$$\lambda = C(1 - e^{-\left(\frac{t}{\beta}\right)^{\alpha}}) \tag{5}$$

where C is a real valued coefficient, $t \geq 0$ denotes the quarter and λ denotes the expected number of failures in quarter t. Accordingly, the parameters of this estimation model obtained by using nonlinear least square method in Matlab curve fitting environment are given in Table 1.

Table 1. Parameters for the Estimation Model

Type	α	β	C
1	6.4502	2.5093	19.9360
2	9.8969	1.0754	32.2871

Figure 2 and Figure 3 show estimated mean failure rates and average actual failure rates for type 1 devices and type 2 devices respectively. In Figure 2, average actual failure rates increases at an increasing rate at first quarter periods. For the remaining time periods, failure rate increases at a decreasing rate and it converges after 12 quarter periods. Similarly, in figure 3, part failures increase at early days of product life. For the rest of product life, number of failures keep increasing even after several years of operation. The estimation model seems to provide a good fit for both types of IT devices by face validation; yet a formal validation analysis is provided.

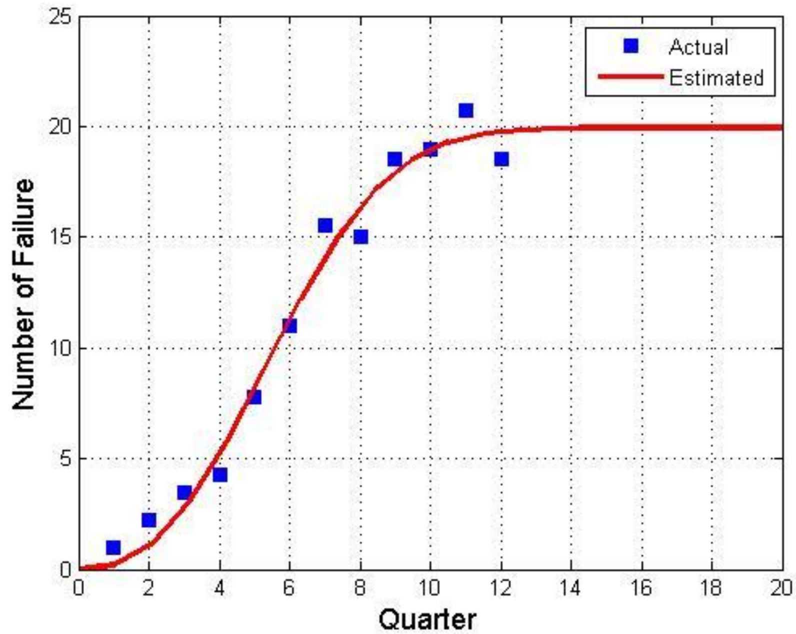

Fig. 2. Estimated mean and average actual failure rates for IT device type 1

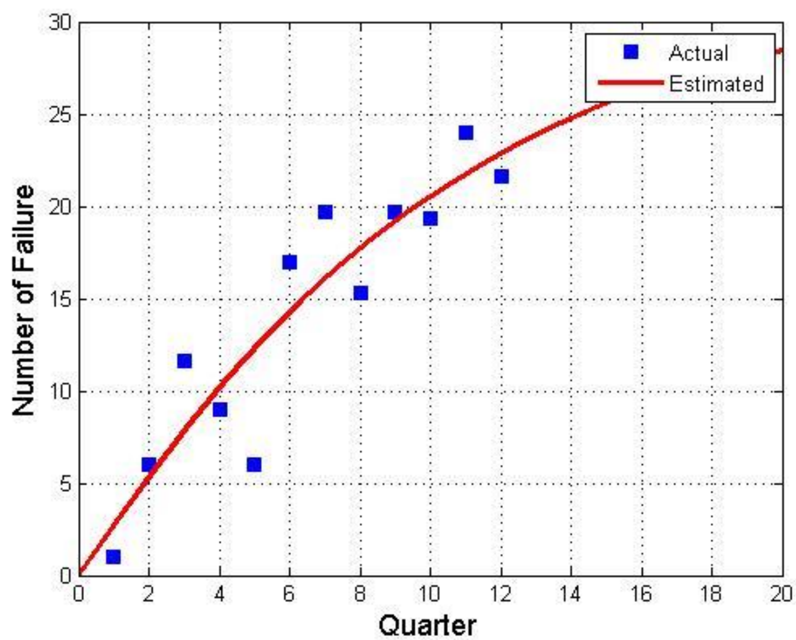

Fig. 3. Estimated mean and average actual failure rates for IT device type 2

4.3 Modeling the failure rates as a Poisson process

It is assumed that failure process is stochastic and it follows Poisson distribution. It can be used to calculate possibilities of an event with given mean failure rate in a period. In other words, a random number with Poisson distribution defines how many such events occur in specified time period. Let's note that in a stationary Poisson process, the mean failure rate λ is constant in all periods. However in our problem, λ increases and then stabilizes showing that number of failures in a period follow a nonstationary Poisson process. The mean failure rate λ is estimated by the estimation model derived by curve fitting to actual data, as explained above.

The number of failures of an operational disk drive can be modeled according to Poisson distribution (Schwarz et al., 2004). Let *P* be Poisson random variable showing the number of failures in a period, λ be the average failure rate. Poisson probability distribution is given by:

$$P(X = k) = f(\lambda, k) = \frac{\lambda^k e^{-\lambda}}{k!} \qquad k = 0,1,2,.. \tag{6}$$

In addition, it is necessary to clarify exact position of each failure. Given that the number of failures in a period is Poisson distributed with a mean failure rate λ, the time between two consecutive failures follows an exponential distribution with the same rate. Here, Poisson distribution is discrete while exponential is a continuous distribution. Let Y be the duration between two consecutive failures. Then the exponential probability distribution is given as follows for $y \geq 0$:

$$P(Y = y) = f(y, \lambda) = \frac{1}{\lambda}\, e^{\frac{-y}{\lambda}} \tag{7}$$

Exponential random function is used in the simulation model to generate random durations for the days between two consequent failures. Mean failures in each quarter are estimated in each quarter in accordance to the estimation model in Equation 5. Hence we both obtain exact time of failure and total failures in a period.

4.4 Validation of the failure rate estimation models

Validation is to check whether the theoretical model behavior coincides with the actual behavior. The simulation model is run for 100 times and 99% confidence intervals (CI)'s are constructed around the average simulation failure rates as seen in Table 2 for type 1 IT devices.

Table 2. 99% Confidence Intervals for Mean Failure Rate for Device Type 1

Quarter	Actual Average Failure Rate	Estimated Mean Failure Rate	Simulation Average for Failure Rate	Sim Min	Sim Max	Lower Limit of 99% CI for Failure Rate	Upper Limit of 99% CI for Failure Rate
1	1	0.1846	0.15	0	1	0.04	0.26
2	2.25	1.0283	0.78	0	4	0.5	1.06
3	3.5	2.7164	2.71	0	7	2.24	3.19
4	4.25	5.1892	5.47	1	13	4.72	6.21
5	7.75	8.1756	8.18	1	16	7.35	9.01
6	11	11.2774	11.29	4	19	10.22	12.35
7	15.5	14.0963	14.40	6	30	13.01	15.78
8	15	16.3539	15.55	6	28	14.33	16.77
9	18.5	17.9509	19.29	8	33	17.99	20.58
10	19	18.9484	19.36	5	29	17.93	20.78
11	20.75	19.4945	19.51	6	33	17.93	21.08
12	18.5	19.7632	19.64	8	32	18.24	21.05
TOTAL	137		136.32			132.41	140.21

Here, we check if the estimated mean failure rates in each period is similar to the actual average failure rates. A simulation model is used to generate nonstationary Poisson failures in each quarter by using the mean failure rates estimated by the model in equation 6. In Figure 4, green and red points represent the upper and lower limits of 99%

CI for failure rates. Blue line is the estimated mean failure rates retrieved from curve fitting algorithm. Blue star label is used to identify actual failure rates for each period in Figure 4.

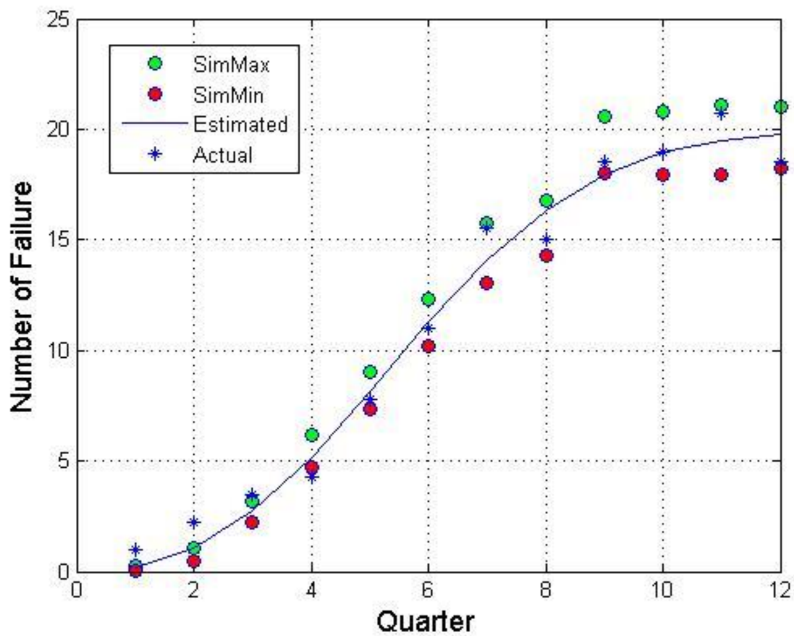

Fig. 4. Simulation confidence interval

Validation of the failure rate estimation model is made by checking if the actual average number of failures is included in the theoretical CI. It is seen that in 8 out of 12 intervals, the actual average failure rate lies in the 99% CI constructed by estimated values. Lower limit and upper limit of confidence interval values are too close to each other considering the low mean average. For instance, in the first period, lower CI is 0,04 and upper CI is 0,24. In real environment, it is impossible as the failure is either one or zero. Hence it can be ignored for the first period.

When the actual average failure rates are placed into graph, it is seen that the performance of the fit is less satisfactory in the first years and gets much better after the 4th quarter. One reason for this weakness might be attributed to the fact that low level of errors are encountered in the first quarters, i.e., maximum 2 failures occur in the first quarter whereas it increases up to 36 in the next quarters. Similarly we provide the validation analysis for type 2 IT devices in Table 3.

Table 3. 99% Confidence Intervals for Mean Failure Rate for Device Type 2

Quarter	Actual Average Failure Rate	Estimated Mean Failure Rate	Simulation Average for Failure Rate	Sim Min	Sim Max	Lower Limit of 99% CI for Failure Rate	Upper Limit of 99% CI for Failure Rate
1	1	2.6311	2.56	0	6	2.21	2.91
2	6	5.2952	5.20	1	11	4.64	5.76
3	11.66	7.8126	7.85	2	14	7.15	8.55
4	9	10.1515	10.19	3	19	9.32	11.06
5	6	12.3055	12.30	5	22	11.40	13.20
6	17	14.2782	14.31	6	24	13.35	15.27
7	19.66	16.0775	15.63	5	27	14.60	16.66
8	15.33	17.7137	17.64	8	31	16.55	18.73
9	19.66	19.1980	18.82	11	30	17.69	19.95
10	19.33	20.5417	21.04	12	36	19.89	22.19
11	24	21.7562	21.74	11	37	20.41	23.07
12	21.66	22.8521	22.46	14	36	21.35	23.57
TOTAL	170.33		169.74			165.64	173.84

4.5 Structure of inventory control models

To handle the inventory control model described above, two inventory control policies are considered: i) continuous-review (Q, r) and ii) periodic review (S, s) inventory control systems. These inventory control systems are explained in detail in order to identify advantages and disadvantages between alternative solutions. Both systems can be suitable considering the effects on total costs.

4.5.1 Continuous review (Q, r) policy

Continuous review model provides two decision variables that refers to reorder level, *R*, and order size, *Q*. Whenever number of IT spare parts located at inventory decreases to *R*, spare parts of size *Q* are ordered, otherwise no orders are given. Then, the order size *Z* is calculated according to the Equation 8:

$$Z = \begin{cases} Q, & if\ \ X_t \le r \\ 0, & if\ X_t > r \end{cases} \tag{8}$$

If part quantity of current inventory is less than or equal to reorder point r, new order is placed with constant size of order Q. (Q, r) policy is advantageous due to shorter replenishment time, however it increases total costs.

4.5.2 Periodic review (S, s) policy

Periodic review model provides two decision variables that refers to order-up-to level S_t and minimum order level s_t. Let Z_t be order size where t is current time period. X_t is defined as current inventory level, S_t is defined as order up-to level and s_t is defined as minimum order level. Order size parameter is calculated at the beginning of each time period according to Equation 9:

$$Z_t = \begin{cases} S_t - X_t & if\ s_t \ge X_t \\ 0 & if\ s_t < X_t \end{cases} \tag{9}$$

IT spare part inventory level is checked periodically for (S, s) policy. If number of IT spare parts is less than minimum order level s_t, new order is placed in order to increase level of inventory up to specified level.

CHAPTER 5

SIMULATION MODEL

In order to determine total cost and service level performance for any selected inventory control policy, a simulation model is developed in MATLAB tool. Initial settings related to existing IT device information are read by user interface from a MS Excel file. The same interface is used to enter the parameters related to inventory level and simulation run settings. After initialization step, the model calculates total cost and service level performances for each inventory management scenario.

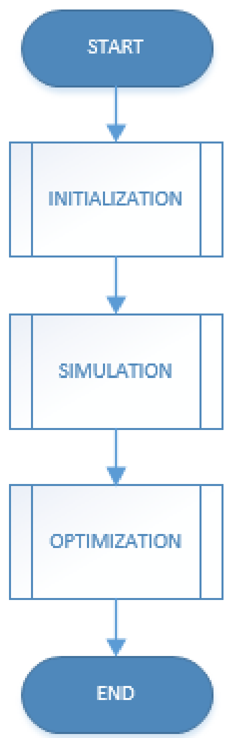

Fig. 5. General flow of the simulation models

This chapter contains parameters and the performance measures. Next, the algorithm of the simulation model is explained. Lastly, an algorithm is proposed to optimize the decision variables of the selected inventory control policy which were assumed to be parameters in the simulation model.

5.1 Definition of the parameters and performance measures

Parameter definition flow chart of the simulation model is given in Figure 6. Firstly, inventory control policy and simulation start time period are chosen. Next, initial information such as IT spare parts on hand and number of runs are entered. IT device file must be filled out at this step. Then, the file is selected and details such as age and type information are extracted from the file. It can be confirmed from command line. Next mean demand is estimated for each IT device and total demand of IT spare part is calculated for each quarter. Total demand information is stored for further reference. Then, the initial values of the two decision variables are entered together with an increment size to be used to generate alternative scenarios for the optimization to be explained later.

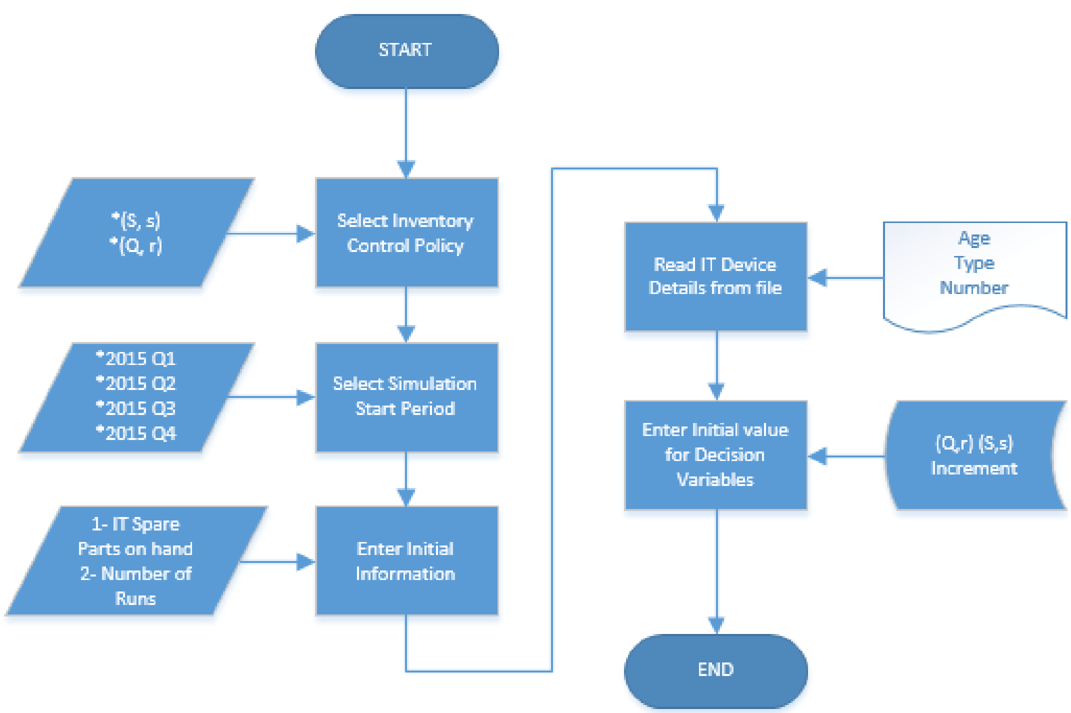

Fig. 6. Initialization of the simulation model

One period is assumed to be one quarter of a year. Initial parameters and functions are defined as follows:

TimePer: Simulation Start Period n, n=1, 2

InitInvSize: Initial Inventory on Hand

ActInvSize: Number of available IT spare parts

IncSize: Increase/decrease size between each option *i*

PolType: Policy Type which is either (Q, r) or (S, s)

DV1: First decision variable minimum option (*S* or *Q* depending on policy type)

DV2: Second decision variable minimum option (*s* or *r* depending on policy type)

TotRun: Total Number of Runs

TotFail: Total Number of Failures (failures/time period)

TotCost: Total Cost of Service Company

SerLev: Service Level Performance

ActRun: Active Number of Simulations

OrdTime: Regular Order Lead Time (days)

OrdSize: Size of Regular Order (number of IT spare parts)

PenCost: Out of Stock Cost ($/penalty)

OutStock: Number of Stock-out issues

OrdCost: Regular Order Cost ($/order)

C: Unit Storage Cost ($/part/day)

Days: Days between Consecutive failures

File_name: IT Device Details File Name

File_path: IT Device Details File Path

SceID: Alternative Scenario Identity (ID)

PushButton1: Optimize the total cost

ToggleButton: Choose IT spare part details file

In addition, output performance measures are listed:

MinTotal: Minimum Average Total Cost TC_t

MaxSerLev: Maximum Average Service Level SL_t

5.2 Algorithm of the simulation model

Next, a simulation model is developed to execute the events and update the performance measures. Figure 7 shows the failure events and regular order receival which are processed during simulation. When a failure occurs, a spare part is used from the inventory and inventory costs are updated. When the (Q, r) policy is selected, a new order of size Q is placed for the spare parts if the inventory level is less than r and the order receival time is determined. In case of a stock out, emergency order is given where the penalty cost is charged.

When a new order is received, then the inventory level is updated. If the (S,s) policy is selected, then the inventory level is checked at the beginning of every period and an order is placed, if the inventory level is less than *s*. The following updates are made according to the events of the simulation.

1) When a regular order is placed, total cost is updated as:

$$[\text{TotCost}] = [\text{TotCost}] + [\text{OrdCost}]$$

2) When there is a failure, storage cost of IT spare parts inventory is charged

$$[\text{TotCost}] = [\text{TotCost}] + C \times [\text{ActInvSize}] \times [\text{Days}]$$

3) When an emergency order is placed, an extra penalty cost [Penalty] is charged.

$$[\text{TotCost}] = [\text{TotCost}] + [\text{Penalty}]$$

The level of IT spare part inventory [ActInvSize] is updated for these two conditions:

1) When a regular order is received, actual inventory level is updated

[ActInvSize] = [ActInvSize] + [OrdSize]

2) When a failure occurs, the IT spare part is taken from the inventory.

[ActInvSize] = [ActInvSize] – 1

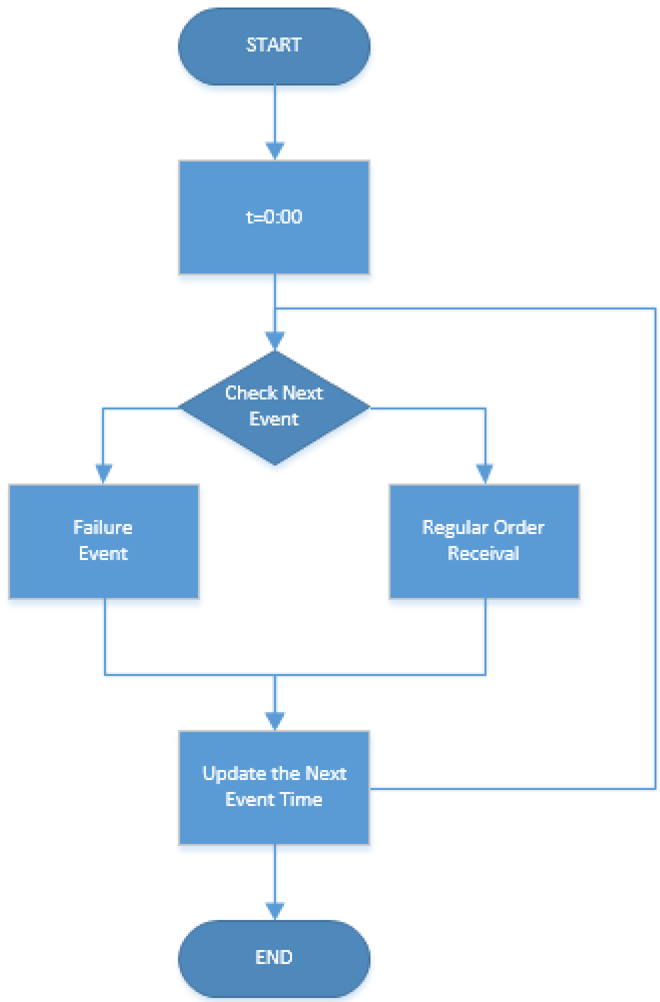

Fig. 7. Simulation events for selected inventory control policy

Simulation events are updated according to the algorithm given in Figure 7. Firstly, time is chosen zero. Then, the algorithm decides the next event which is either a failure event or regular order receival event.

As explained above, the time between two consecutive failures follows a nonstationary Poisson process where the mean demand rate is estimated by an estimation model which is given in equation 5. Also, the total number of stock outs during the simulation [OutStock] are stored for further reference. It is used to calculate service level performance after completing simulation. Service level equation is given:

$$[SerLev] = (1- [OutStock] / [TotFail]) \times 100$$

Lastly, simulation is repeated according to number of runs provided as an input. Number of runs [TotRun] is asked from user at initial step. A progress bar is defined to show instant status of the simulation [ActRun]. After multiple runs are made, average performances for total cost [TotCostAv] and service levels [SerLevAv] are calculated and displayed.

5.3 Optimization by using the simulation model

In this section, the parameters of the inventory control policy are considered to be decision variables and the simulation model is used to optimize these decision variables. Alternative scenarios are generated and evaluated for the simulation module. Generation of alternative scenarios module starts by assigning the simulation run number. Initially it is [ActRun=1]. It generates random failures for every run according to the mean demand rate estimated by initialization module. The ending inventory levels, accumulated total costs and other statistics from the previous period are used as the initial settings in the next period. Next, it assigns a unique scenario number for each combination of order quantity, reorder point and time period variables.

For a 4 period simulation, Let Q_i be order quantity and r_j be reorder point where $i,j=1, 2, 3, 4$ are the indices for the alternative values of the decision variables Q and r in any period. k = 1,2,...,65,536 is the index for the Inventory Management Scenario array (IMS) for (Q, r) policy which is defined according to equation 10:

$$IMS\ (k) = \{(Q_i\ r_j)_1^k, (Q_i\ r_j)_2^k, (Q_i\ r_j)_3^k, (Q_i\ r_j)_4^k \mid i=1, 2, 3, 4, \text{ and } j=1, 2, 3, 4\} \quad (10)$$

Similarly, let S_i be order up to level and s_j be lower threshold point. Inventory Management Scenario array (IMS) for (S, s) policy is defined according to the equation 11 for k = 1 to 65,536:

$$IMS\ (k) = \{(S_i\ s_j)_1^k, (S_i\ s_j)_2^k, (S_i\ s_j)_3^k, (S_i\ s_j)_4^k \mid i=1, 2, 3, 4, \text{ and } j=1, 2, 3, 4\} \quad (11)$$

A simulation scenario for 4 periods, consists of 4 choices of Q and 4 choices of r which equals totally 8 choices of decision variables in a scenario. Noting that, there are 4 possible options for Q and 4 possible options for r, total number of alternative scenarios that can be generated is calculated as 4’8 = 65,536. Similarly, the same number of alternative scenarios exist for (S,s) policy optimization.

In any time period t, the minimum values of the first and the second decision variable [DV1] and [DV2] are determined by the user inputs. Inventory management policy can be either (Q, r) or (S, s). The alternative choices of the decision variables are developed by increasing [DV1] and [DV2] by the increments of [IncSize]. For example, if [DV1] = 10 and [DV2] = 5 with [IncSize] = 1, there are 4 alternative choices for array Q_i = [10,11,12,13] and there are 4 alternative choices for array r_j =[5,6,7,8]. In 4 period simulation, the generated scenarios IMS(k), k = 1, 2, …, 65,536 are listed:

IMS(1)=(10,5)(10,5)(10,5)(10,5);

IMS(2)=(10,5)(10,5)(10,5)(10,6);

…

IMS(65,536)= (13,8)(13,8)(13,8)(13,8)

In Figure 8, the generation of alternative scenarios and the optimization algorithm is explained in more detail. The simulation is run for 4 periods where the time period starts from 1 and ends at 4. In the first period, selected inventory control policy is simulated for one scenario during the first time period. Then, there is an increment for scenario number and the simulation repeats for another scenario during the first time period.

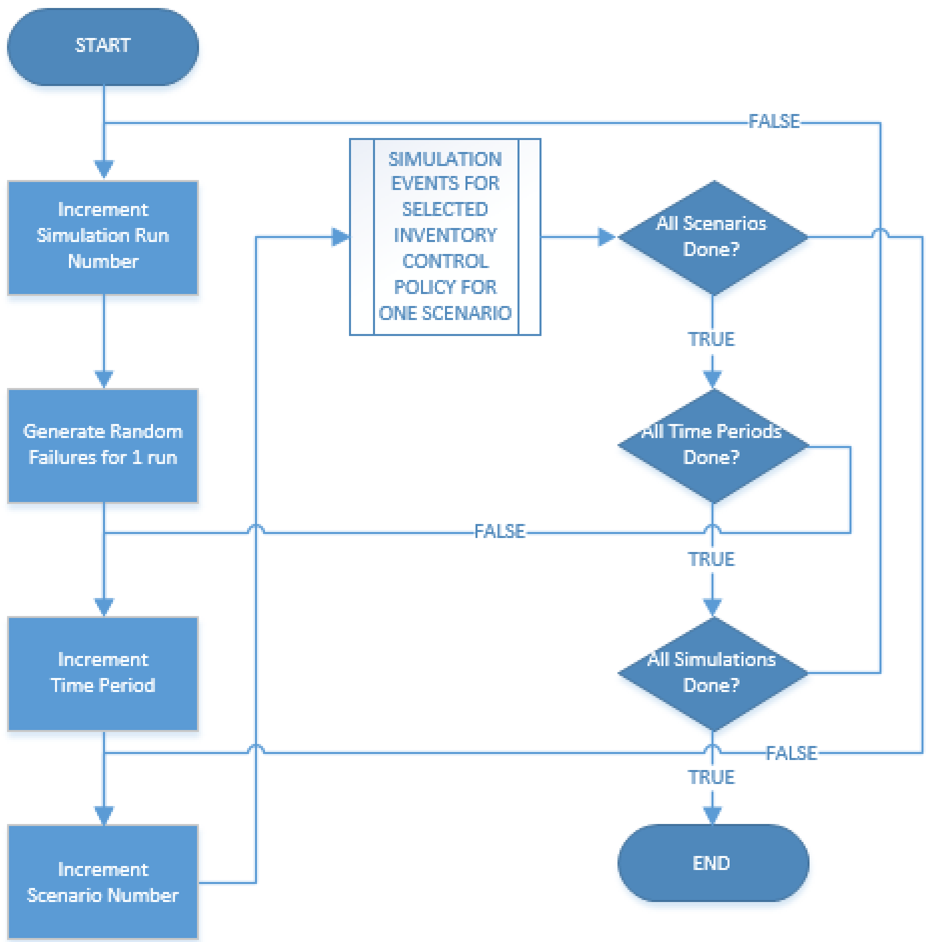

Fig. 8. Generate alternative scenarios for selected inventory control policy

After finishing the last scenario for the first time period, it passes to increment for time period section. In this part, the first period scenario statistics are used as the initial settings for the second period scenarios. When time period is increased to 4, IMS is obtained for the first simulation run. After finishing all scenarios for all time periods, simulation run increment is processed and new random failures are generated.

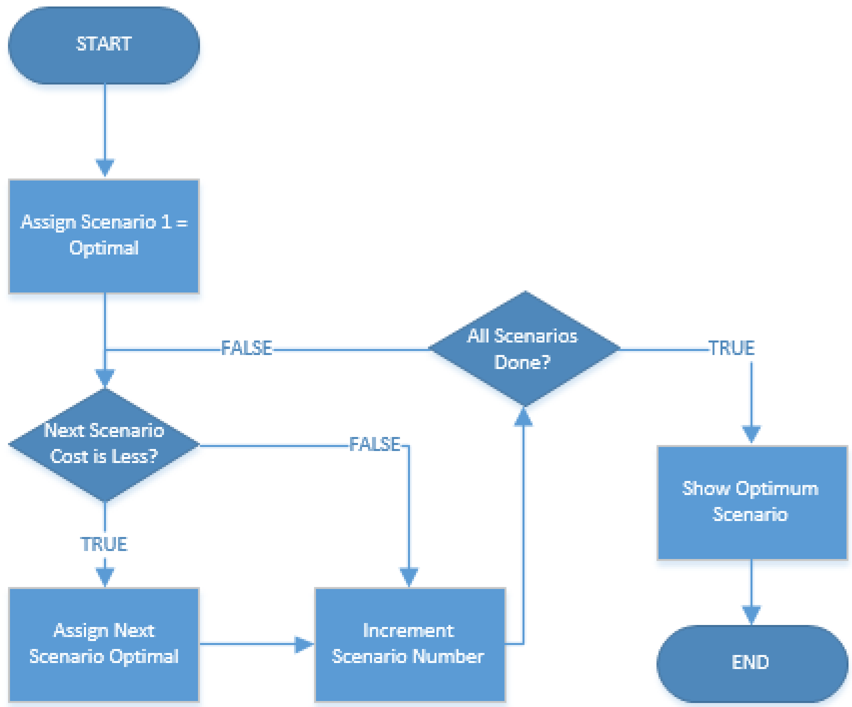

Fig. 9. Evaluate alternative scenarios for the selected inventory control policy

Above mentioned steps are repeated for the new run. When all simulation runs are completed, average cost values and service levels are calculated for each inventory management scenario. The results provide optimal decision variables for each time period. In Figure 9, optimum scenario is determined by evaluating the alternative scenarios for 4 time periods. Firstly, IMS 1 is assigned as optimal and the algorithm checks whether the next scenario has better results. If the next scenario has less cost, it is assigned as the optimal IMS. This process repeats until the last IMS is checked. The optimum IMS is shown and figured for each period.

CHAPTER 6

DECISION SUPPORT SYSTEM

Integrating a DSS into the current simulation model enables the service company to evaluate the periodical demand of the IT spare parts easily. The DSS provides efficient, effective and flexible decision making environment for managers. It also calculates the optimal inventory policy type, order quantity and reorder level considering given initial settings. In order to increase usage of the simulation model, a graphical user interface (GUI) is designed by using Matlab guide function. Figure 10 shows the blank GUI which provides easier usage for end customers.

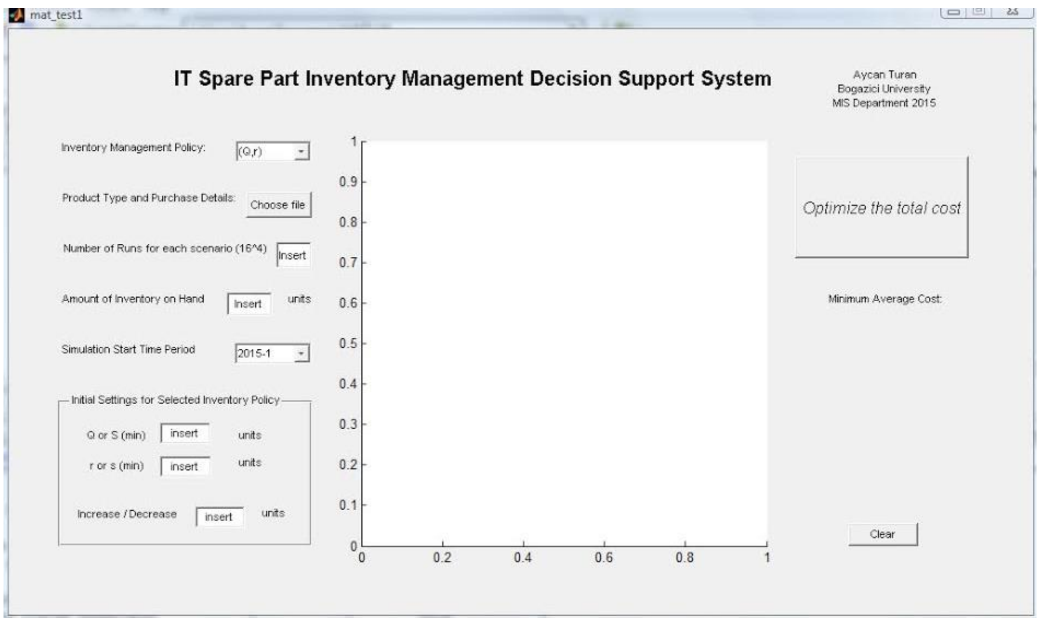

Fig. 10. DSS GUI start screen

The GUI must be run according to the workflow of the DSS which is shown at Figure 11. Firstly, user enters number of runs for each scenario [NumberSim] and number of IT spare parts on hand [CurStok] input variables. Preferred inventory control policy [PolType] and simulation start time period [TimePer] must be chosen among alternatives.

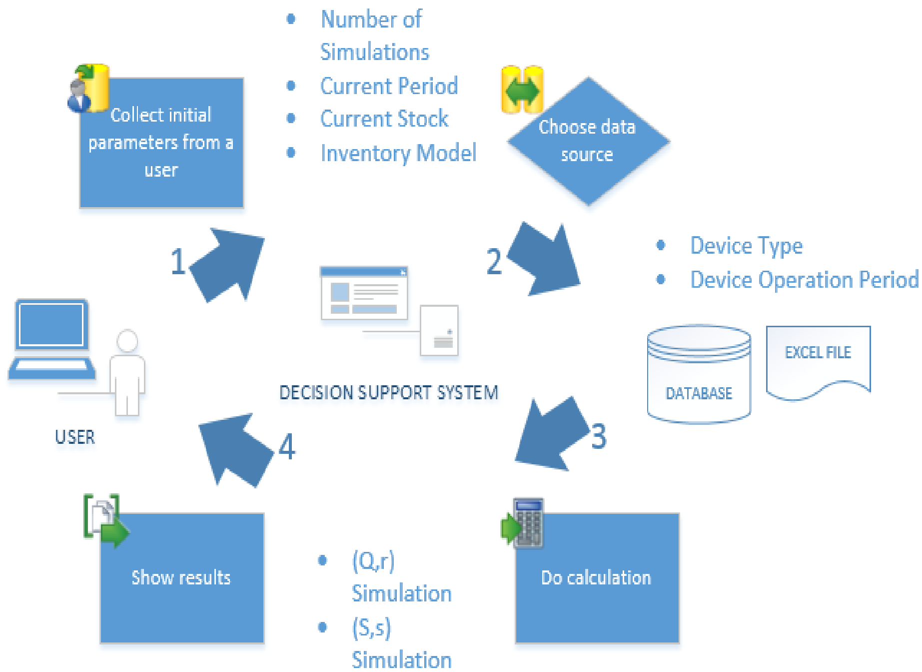

Fig. 11. DSS workflow

6.1 Optimization by simulation

As a first step of optimization process, IT device details file must be selected by clicking on the choose file button [ToggleButton]. Product type and IT device age details are read from Microsoft Office Excel file. The content of a sample input file is given in Table 4.

Table 4. Sample Content of IT Device Details File

NoProdPromt	ProductType	PurchaseYear	PurchaseHalfYear
1	1	2013	2
2	1	2014	2
..	..	..	..

The DSS stores file name [File_name] and file path [File_path] information and reads device type and device age information. Lastly, minimum values of decision variables [DV1] and [DV2] must be entered and the increment size [IncSize] must be inserted to increase/decrease box. After completing initial settings on GUI, user must click on "Optimize the Total Cost" button [PushButton1] to start calculations. Then, a progress bar appears and it shows instant completion rate of simulation according to the finished iterations rate, as seen in Figure 12. Sample command line output is given in Appendix A. Detailed progress can be seen via command line which is shown in Appendix B.

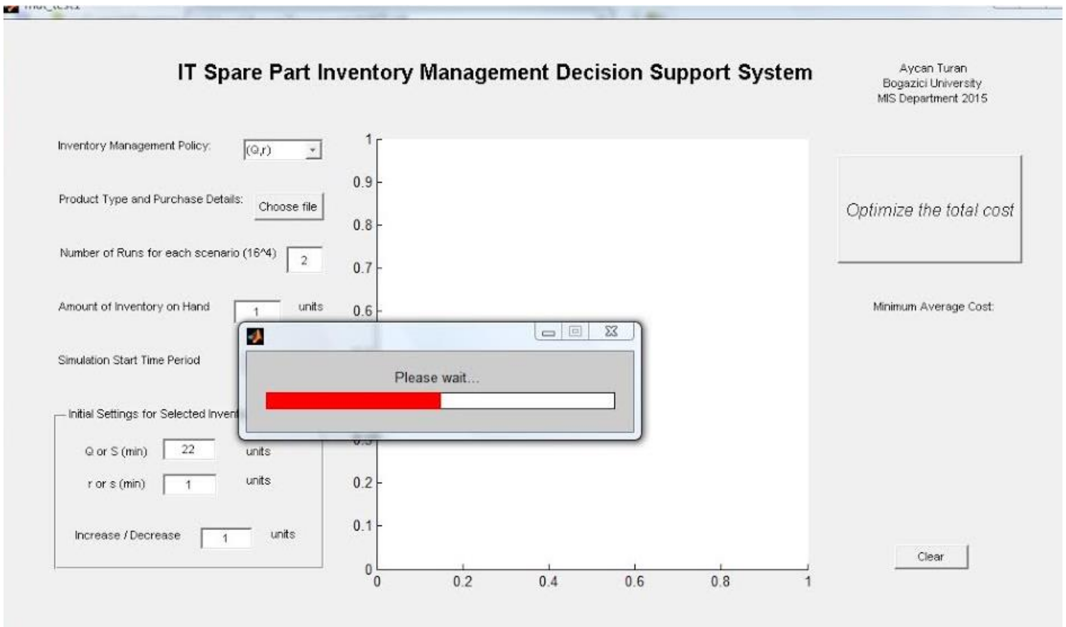

Fig. 12. Progress bar of GUI

At the end of the simulation, total cost and service level performance results are shown on the right side of the GUI. Moreover, the optimal decision variables of the selected inventory policy is shown in the axes. If optimal points are at the minimum or maximum boundaries of the Q_i and r_j, the user should update the [DV1], [DV2] and/or [IncSize] to generate new search regions for the decision variables. When the simulation is re-optimized with new parameters, it is figured in different color. For instance, the first simulation results are shown in red, second one is in blue and the third one is shown in green.

When the DSS is started from GUI, it provides easier decision making environment since the previous simulation results can be seen both numerically and graphically. The simulation environment allows us to make what-if analysis. For example, the impact of initial spare part inventory can be examined by updating amount of inventory on hand parameter. A clear button is added to GUI to clear initial settings before changing policy type. Figure 13 shows the final version of results GUI after three simulation runs.

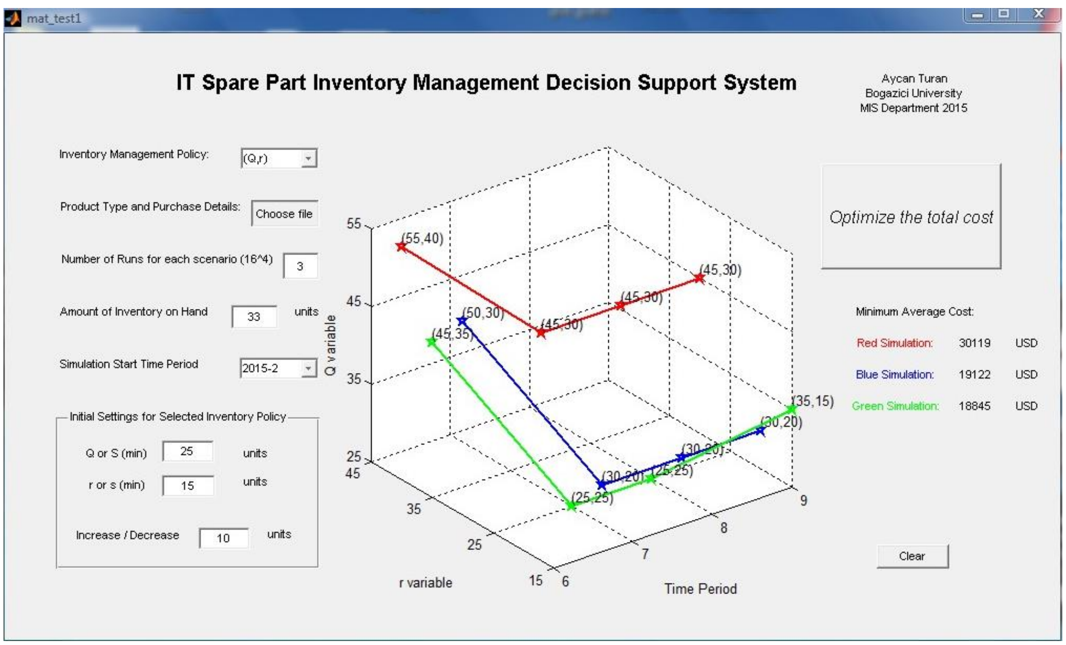

Fig. 13. Results GUI after three simulation runs.

In Figure 14, sample test scenario is applied into the DSS. The scenario consists of 4 IT devices which has different ages. In the first run, it costs $145,622 which is much more than expected. Considering the extremely high cost of the first run, it is said that the reason could be due to the out-of stock issue. For instance, stock-out may occur in case of low initial inventory. Even if the regular order is processed in the first day, the delivery takes one order lead time duration which is equivalent to 30 days for the sample scenario. Between this time duration, existing spare parts inventory must be high enough to supply demand for at least 30 days. In previous example, stock-outs occurred for given initial settings. When the simulation is repeated with only increasing on hand spare part inventory, demand is successfully supplied from on hand inventory without any out-of-stock problem. The total cost decreases from $145,622 to $22,936 which is more than 80 percent. It clearly shows the significance of out-of stock problem as well.

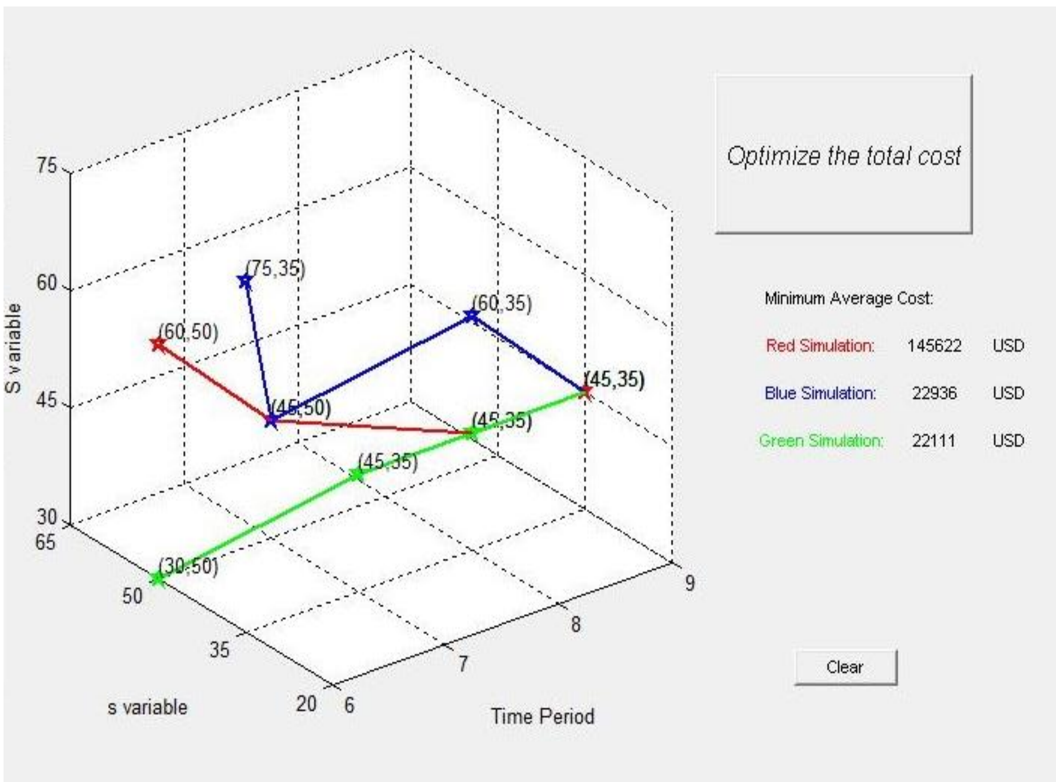

Fig. 14. Results under stock-out problem.

CHAPTER 7

RESULTS AND DISCUSSIONS

In this section, the DSS is tested under various input settings to improve recommended inventory policy solution based on (Q, r) and (S, s) inventory control policies. The DSS repeats simulation runs 10 times for any given input settings that is referred to a scenario. When the simulation is run with initial parameters, first results are generally not satisfactory enough. Hence, the input settings are updated considering the results to find the optimal solution. After two or three tests, the solution is optimized according to total cost and service level variables.

Next, experimental design is made to test the sensitivity of the initial configuration parameters which are unit storage cost, penalty cost and regular order cost. Cost and service level performances of both (Q, r) and (S, s) policies are compared in MATLAB simulation environment.

7.1 Illustration of the DSS with (Q, r) policy

We proposed a sample test scenario to apply the DSS into real environment. In that test scenario, “Number of Runs” equals to 10, “Current Time Period” equals to the first quarter of 2015 and “Number of Spare Parts on Hand” equals to 30 units. According to sample test scenario, four devices are operational simultaneously at company datacenter. Three of these devices are purchased in 2014 in different quarters and the last one is purchased in the first quarter of 2015. Three of sample devices belong to type one and the last one belongs to type two. Hence, expected failures must be considered carefully for each device and purchase quarter combination. More than four devices can be included in the text to extend coverage. Detailed purchase time period and product type information of sample test are given in Table 5.

Initial settings are provided as follows:

- Unit Storage Cost = 1($/unit)
- Penalty cost = 1000 ($/stock out)
- Regular order cost = 100 ($/order)

Table 5. IT Device Details File Index

No	ProductType	PurchaseYear	PurchaseQuarter
1	1	2014	2
2	1	2014	3
3	2	2015	1
4	1	2014	4

Table 6 summarized the optimization tests made in the DSS environment. For the first test, continuous review policy is chosen with minimum parameters (Q, r) equals to (20, 10) with an increment size of 10. Hence, $Q_i \in \{20, 30, 40, 50\}$ and $r_j \in \{10, 20, 30, 40\}$ can be seen in the second and third columns in Table 6. According to the first test results, optimized IMS is defined by (Q_i, r_j) option numbers 6, 16, 16 and 16 for period 1-4 respectively. Hence the optimal IMS is realized as {(30, 20) (50, 40) (50, 40) (50, 40)} for four periods. Minimum total cost is calculated $27,486 with a service level of 0.995.

Next, it is suggested to check if the optimal solution is higher than the upper limit of the first test. Regarding the IMS of the first test, (Q) value and (r) value are at the boundary of the search region where (Q_i, r_j) = (50, 40). Boundary points are identified by red background cells in Table 6. It is recommended to apply tests again with updated parameters which is shown in column 4-5 of Table 6.

For second test, continuous review policy is chosen with minimum parameters (Q, r) equals to (30, 20). Second test results indicate that optimized IMS is a combination of option numbers 5, 15, 16 and 4 for time period 1-4 respectively which equals to IMS=(40,20)(60,40)(60,50)(30,20).

Table 6. Continuous Review Policy Tests

Test No	1		2		3		4	
Policy	Q	R	Q	r	Q	r	Q	r
(Q_i, r_j) Option	20,30, 40,50	10,20, 30,40	30,40, 50,60	20,30, 40,50	35,45 55,65	25,35, 45,55	40,50, 60,70	30,40, 50,60
1	20	10	30	20	35	25	40	30
2	20	20	30	30	35	35	40	40
3	20	30	30	40	35	45	40	50
4	20	40	30	50	35	55	40	60
5	30	10	40	20	45	25	50	30
6	30	20	40	30	45	35	50	40
7	30	30	40	40	45	45	50	50
8	30	40	40	50	45	55	50	60
9	40	10	50	20	55	25	60	30
10	40	20	50	30	55	35	60	40
11	40	30	50	40	55	45	60	50
12	40	40	50	50	55	55	60	60
13	50	10	60	20	65	25	70	30
14	50	20	60	30	65	35	70	40
15	50	30	60	40	65	45	70	50
16	50	40	60	50	65	55	70	60
Optimum IMS	6,16,16,16		5,15,16,4		9,11,16,8		1,11,7,8	
Cost	$27,486		$18,329		$14,454		$14,189	
SerLev	0.995		1.000		1.000		0,999	
Improve	NA		33,2%		21,1%		1,8%	

Minimum total cost is calculated $18,329 with a service level of 1.000. The total cost is improved 33.2% compared to the first test. When we investigate IMS in test 2, decision variables are listed mostly at upper limit (Q, r) equals to (50, 40). It is seen that the optimal solution is still at the boundaries. In order to improve results, the upper bounds for (Q_i, r_j) are further increased in test 3.

When we repeat the test with updated parameters that minimum (Q, r) equals to (35, 25), the total cost of the third test is decreased to $14,454 with an improvement of 21,1%. Figure 15 shows optimal IMS points of the third test and the fourth test. Considering the third test, boundary points are still improvable.

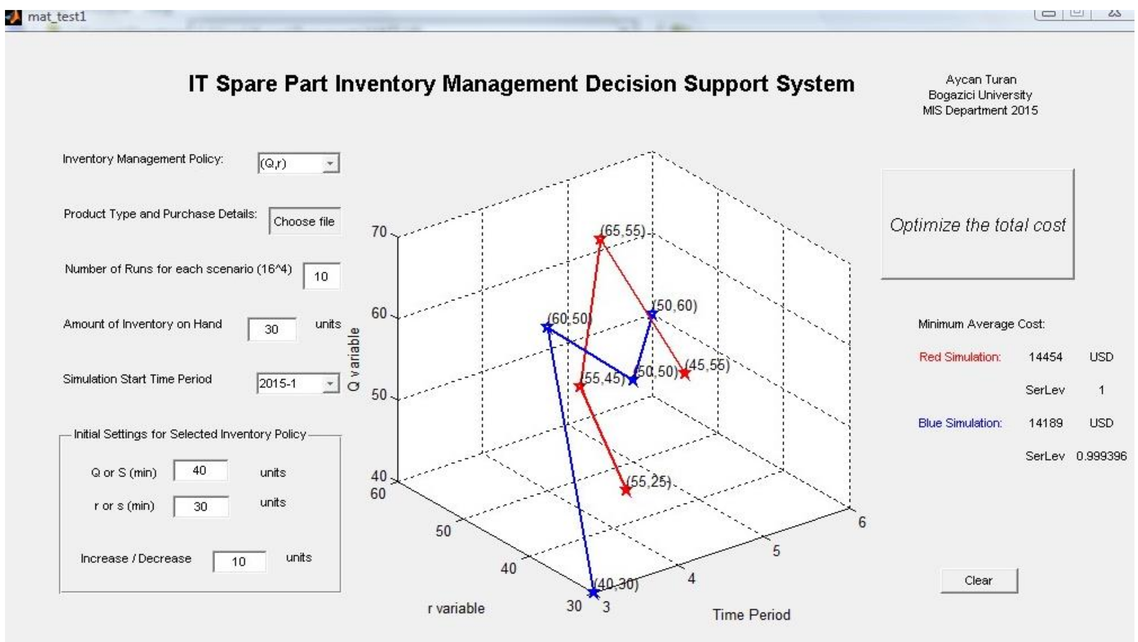

Fig. 15. Test results of (Q, r) optimization policy

The test is repeated with updated parameters one more time. Minimum parameters of the last test (Q, r) equal to (40, 30). It provides a relatively low decrease for total cost with an improvement of 1,8%. Hence, it is seen that the best result of test 4 is satisfactory considering the total improvements based on service level and total cost. Optimal total cost is estimated $14,189 with a service level of 0.999. Optimal IMS of the last test of (Q, r) policy is as follows:

- IMS= (40, 30) (60, 50) (50, 50) (50, 60)

7.2 Illustration of the DSS with (S, s) policy

After the simulation optimization part of continuous review policy, periodic review policy option is chosen. When we repeat tests for (S, s) policy, optimum results are provided after third test. For the first test of periodic policy, mean parameters are chosen (30, 20). Cost is extremely high compared to continuous review methodology. One of the reasons of high cost is identified as lower service level which is calculated 0,961. In spite of the stock out problems occurred during the first test of (S, s) policy, it is possible to improve cost and service level results with updated starting values. Since the first test results are around upper bound points, both (S, s) minimum values must be increased. It is recommended to increase number of core points in the cube shown in Figure 16.

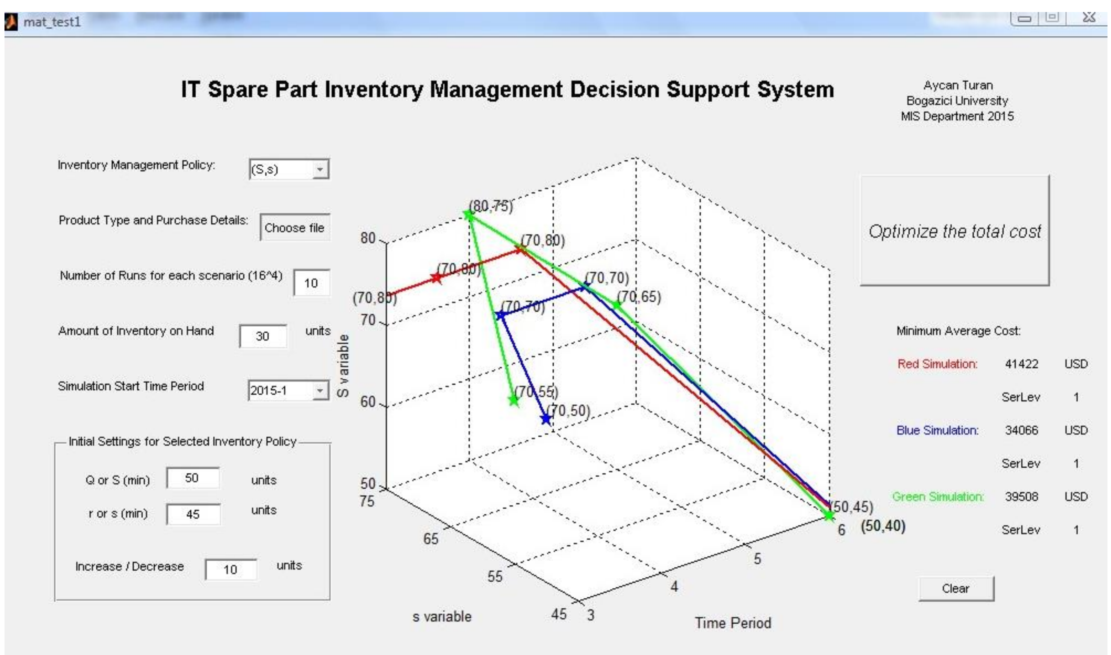

Fig. 16. Test results of (S, s) optimization policy

When we rerun the simulation with updated minimum parameters (50, 40) and increment size 20, the cost is decreased to $41,422 that indicates a improvement ratio of 70,2% compared to the first test. When the boundaries of IMS is examined, all the points of the first run are listed red in Table 7.

Table 7. Periodic Review Policy Tests

Test No	1		2		3		4	
Policy	S	S	S	s	S	s	S	s
Policy values	30,40 50,60	20,30 40,50	50,70, 90,110	40,60, 80,100	50,60, 70,80	40,50, 60,70	50,60, 70,80	45,55 65,75
1	30	20	50	40	50	40	50	45
2	30	30	50	60	50	50	50	55
3	30	40	50	80	50	60	50	65
4	30	50	50	100	50	70	50	75
5	40	20	70	40	60	40	60	45
6	40	30	70	60	60	50	60	55
7	40	40	70	80	60	60	60	65
8	40	50	70	100	60	70	60	75
9	50	20	90	40	70	40	70	45
10	50	30	90	60	70	50	70	55
11	50	40	90	80	70	60	70	65
12	50	50	90	100	70	70	70	75
13	60	20	100	40	80	40	80	45
14	60	30	100	60	80	50	80	55
15	60	40	100	80	80	60	80	65
16	60	50	100	100	80	70	80	75
Optimum IMS	16,16,16,1		7,7,7,1		10,12,12,1		10,14,12,1	
Cost	$139,105		$41,422		$34,066		$39,508	
SerLev	0,961		1		1		1	
Improve	NA		70,2%		17,7%		-15,9%	

In Table 7, boundary points are shown red and core points are shown yellow. For the second run, the increment size is decreased to 10 and the test is repeated with the same minimum (S, s) parameters (50, 40). When the simulation run is repeated, number of red boxes decreased to 2. In the third run, it is increased to 3, however the optimum solution is provided in the third test. Hence, it is said that close results must be checked before deciding the solution. All IMS variables of periodic review tests are listed in Table 7. Minimum cost result which is obtained at the third run is given as:

- IMS(S, s) = (70, 50) (70, 70) (70, 70) (50, 40)

7.3 Experimental design

From customer's point of view, this section contains valuable information as the inventory control parameters fluctuate independently from each other. One needs to know how sensitive the optimal inventory control policy is with respect to estimated parameters. Unit storage cost, stock-out penalty and regular order costs are the main parameters to determine the best inventory control policy.

In this section, the effects of the changes in the basic parameters namely unit storage cost, penalty cost and regular order cost on the optimal total costs and service level are analyzed. Two values, high and low are defined for each parameter and accordingly 2^3 equal to 8 input scenarios are generated. For each scenario, the DSS is used to determine the optimal inventory control policies for (Q, r) and (S, s) strategies respectively. The results are summarized in Table 8.

The first parameter is unit storage cost which equals to either \$1/unit/day or \$2/unit/day. The second parameter is the fixed penalty cost which can take values low \$1000 or high \$5000. The third parameter is order cost which is low \$100 or high \$500. As each parameter change can update the optimized value of inventory control policies, it is recommended to run the simulation with updated parameters. The first test plan includes $1 storage cost of one spare part per day, $1K penalty cost and $100 fixed order cost. Total cost results are given in Table 8. In each plan, all combinations are assigned to measure effects accurately. For instance, unit storage cost of test plan 1 is determined low value as 1$. When test plan 2 is examined, it is shown that the plan 2 has high unit cost value of 2$ in order to figure out how storage cost variance effects policy types in terms of total cost and service level.

Table 8. Experimental Design Results

Test Plan	Unit storage cost ($)	Penalty cost ($)	Regular Order cost ($)	SerLev (Q, r)	TotCost (Q, r)	SerLev (S, s)	TotCost (S, s)	Diff (Q, r) / (S, s)
1	1	1K	100	0,999	14,189	1	15,380	0,92
2	2	1K	100	0,999	30,934	0,998	31,219	0,99
3	1	5K	100	0,998	17,431	1	11,574	1,51
4	2	5K	100	1	37,307	1	29,915	1,25
5	1	1K	500	1	18,107	1	17,511	1,03
6	2	1K	500	1	32,544	0,999	32,688	0,99
7	1	5K	500	1	18,993	1	17,684	1,07
8	2	5K	500	1	30,753	0,999	26,644	1,15

Test plan 3 shows penalty effect on total cost. Plan 4 aims to determine the best possible option in case of high storage cost and high penalty. Plan 5 represents low storage cost, low penalty and high regular ordering cost test. Only difference of plan 6 is high storage cost compared to test plan 5. When plan 7 is compared with plan 8, the unit storage cost difference can be identified in case of high penalty and high regular order cost. As stated above, optimal solution depends heavily on initial variables.

CHAPTER 7

CONCLUSIONS

The purpose of this master thesis is to propose a flexible, efficient and effective DSS for the inventory management of IT spare parts. To fulfill this purpose, failure estimation methods and alternative inventory management strategies are examined in detail. Outputs of the prediction strategy is tested and validated under different conditions. In addition, alternative inventory management policies are examined and coded in simulation tool. Therefore, a simulation-based DSS is developed based on the findings of inventory management and failure estimation work. It is designed for one of the biggest computer infrastructure providers in Turkey. It provides customer service managers the ability to make better decisions. Also, it is shown that continues review and periodic review methods are both convenient for different test conditions according to starting parameters and number of devices in operation.

In this study, the DSS is developed by using MATLAB version 2007 R2 which is installed at a Windows Vista operating system computer. Next, a GUI is developed for the efficient use of the DSS. The managers interact with the GUI easily and change the input values to investigate the optimum solution for different policies. One of the most important outputs of the DSS is to clarify optimum inventory model by performing what-if analysis under different conditions. In this work, two different inventory management policies are evaluated and both are optimized according to given initial settings. For instance, if regular order cost and penalty cost are low, continuous review method is superior. On the other hand, periodic review solution can obtain less costly results in case of high cost settings. As a result, the DSS can be used as a learning tool that provides efficiency resulting low cost and high service levels. In addition, total process time is decreased by completing code definitions at initial step. Hence, the DSS is defined as an efficient tool considering the improvements based on time.

The effectiveness of the DSS is enhanced by several features. Easy-to-use input screen, optimize push button, graphical output screen, total cost and service level output screen are major advantages that provides efficiency for end-users. It provides easy and faster comparison of results as the whole data can be shown on the screen simultaneously. For instance, the first results remain in the GUI when the simulation run is repeated. The first and the second run results are shown as well, if the simulation is run for three times. Also, graphical outputs are provided in different colors for each run. From decision maker's point of view, it provides effectiveness by focusing on graphical interface and comparison of results. In addition, a process bar is added to give customer valuable information regarding the instant status of simulation run.

The DSS also provides flexible decision making environment as it considers all devices listed at inventory file independent from age and type. Number of devices, types of devices and operational ages of devices are several features that are supported in the DSS. The DSS provides optimal control of IT spare part inventory for multiple device operations. For instance, different types of IT devices are supported if they use the same IT spare part. Therefore, inventory policy is simulated based on the dynamic behavior of real spare part demand. In case of cost-related changes, DSS settings can be updated easily via GUI. When the simulation is repeated with updated settings, results will be updated and the DSS will provide optimum IMS after several simulation runs. The DSS is used to estimate the optimum control policy for four quarters by evaluating 65,532 alternative IMS.

As future work, the DSS environment may be improved to operate faster with more features. As an example, this study gives opportunity to make a further data analysis on error logs of IT devices. Hence, the other type of errors can be listed and they can be used to model different kind of spare part demand such as power supplies or memory modules. Further research subjects are identified in various areas such as lead time fluctuations and spare part variations. A research question could be studied regarding the spare part type variation when modelling failures and total cost. Developing more detailed tools and validating with practical results enable companies to decrease operational costs. It helps the managers to evaluate the results more accurately.

APPENDIX A

SAMPLE CLI OUTPUT

```
IT spare part inventory DSS v11

Please copy inventory database folder to MATLAB Current Directory
Press ENTER when finished
 4 quantity of product uploaded
No= 1: ProductType= 1 InstallPeriod= 1
No= 2: ProductType= 1 InstallPeriod= 2
No= 3: ProductType= 2 InstallPeriod= 3
No= 4: ProductType= 1 InstallPeriod= 2
Inventory policy options:
-1- for continuous review (Q,r) system
-2- for periodic review (S,s) system
Please enter policy code: 1
Please enter number of simulations: 20
Please enter current time period: 4
Please enter current stock quantity: 15
Please enter medium Q value: 30
Please enter medium r value: 20
 1.simulation started!!
loop 1.simulasyon ve  1.period started
….
20 Simulation result average min scenario 65740. scenario costs 26995$
!!!!  65740. senaryo: ! 12., ! 12., ! 16., ! 15.,

Optimum IMS =
   15    16    12    12

Simulation Failure Average = 385.00
```

APPENDIX B

DETAILED PROGRESS OUTPUT

```
IT spare part inventory DSS v11
Please copy inventory database folder to MATLAB Current Directory
Press ENTER when finished

2 quantity of product uploaded
No= 1: ProductType= 1 InstallPeriod= 1
No= 2: ProductType= 1 InstallPeriod= 2
Inventory policy options:
-1- for continuous review (Q,r) system
-2- for periodic review (S,s) system

Please enter policy code: 1
Please enter number of simulations: 20
Please enter current time period: 3
Please enter current stock quantity: 20

Recommended level Q= 25 and r=15
Please enter medium Q value: 23
Please enter medium r value: 17

loop 1.simulation, 1.period started
loop 1.simulasyon, 2.period started
...
loop 20.simulasyon, 4.period started

!!!! OUTPUT !!!!
!!!!  20770. scenario: !  2., !  2., !  1., !  5., scenario combination (reverse)
!!!! minimum average mean cost  10465$ !!!!

1 scenario has average minimum cost
Senaryo  1 de Q= 17, r=11 dir
Senaryo  2 de Q= 17, r=15 dir
Senaryo  3 de Q= 17, r=19 dir
Senaryo  4 de Q= 17, r=23 dir
```

Senaryo 5 de Q= 21, r=11 dir

Senaryo 6 de Q= 21, r=15 dir

Senaryo 7 de Q= 21, r=19 dir

Senaryo 8 de Q= 21, r=23 dir

Senaryo 9 de Q= 25, r=11 dir

Senaryo 10 de Q= 25, r=15 dir

Senaryo 11 de Q= 25, r=19 dir

Senaryo 12 de Q= 25, r=23 dir

Senaryo 13 de Q= 29, r=11 dir

Senaryo 14 de Q= 29, r=15 dir

Senaryo 15 de Q= 29, r=19 dir

Senaryo 16 de Q= 29, r=23 dir

1.period StErr= 1.02 and RelErr=perc8.9 Mean Total Failure avg = 29.50,

0.99 conf. between min 26.88 and max 32.12!!

2.period StErr= 1.70 and RelErr=perc8.8 Mean Total Failure avg = 49.55,

0.99 conf. between min 45.18 and max 53.92!!

3.period StErr= 1.79 and RelErr=perc6.7 Mean Total Failure avg = 68.15,

0.99 conf. between min 63.56 and max 72.74!!

4.period StErr= 2.62 and RelErr=perc8.8 Mean Total Failure avg = 76.05,

0.99 conf. between min 69.32 and max 82.78!!

20 Simulation result average min scenario 23739.scenario costs 15655$

!!!! 23739. scenario: ! 11., ! 11., ! 12., ! 5., scenario combination (reverse)

Simulation Failure Average = 223.25

0.99 confidence interval failure value between min 213.0144 and max 233.4856!!

23739.senaryo StErr=243.65$ ve RelErr=perc4.0 Mean Total Cost avg = 15655.40$

0.99 confidence interval total cost between min 15029.22 max 16281.58!!

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