WHOLE LIFE COSTING OPTIMISATION WITH INTEGRATED LOGISTICS SUPPORT CONSIDERATIONS

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λ	Failure rate or repair demand
LORA	Level of repair analysis
LRUs	Line repair units
MSO	Maintenance support organisation
MTBF	Mean time between failure
SRUs	Shop replaceable units
$BO_i(S_i)$	Numbers of backorders for item i at the base as function of the stock level
FC	Fixed cost
FCFS	First Come First Serve policy
FMECA	Failure Modes and Effects Analysis
FTA	Fault Tree Analysis
GA	Genetic Algorithms
ILS	The Integrated Logistics Support
ILSP	The Integrated Logistics Support Plan
KPI	Key Performance Indicators
LCDs	Logistic control Numbers
LSA	Logistic support analysis
LSAR	Logistic support analysis record
METRIC model	Multi-Echelon Technique for Recoverable Item Control
MF	Maintenance function
MSF	Maintenance support function
MTBM	Mean time between maintenance
MTTR	Mean time to repair
NPV	Net Present Value of the whole life costs
OEMs	Original Equipment Manufacturers
PBL	Performance Based Logistics agreement
$PBO_i(S_i)$	Backorder probability for item i at the base as function of the stock level
PWA	Present Worth of annual recurring costs
PWN	Present Worth of non-annual recurring Cost
PWOm	Present Worth of One-Off future costs
PWS	Present Worth of Salvage Cost
RAMS	Reliability, availability, maintainability and supportability
RCM	Reliability-Centered Maintenance
RFU items	Ready-For-Use items
S_i	Stock level for item i
TS	Tabu Search Algorithm
VC	Variable cost
WLC	The Whole Life costing Approach
WT	Mean waiting time

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To Amira

My Wife and my Parents

ABSTRACT

It has long been recognised that, in the military sector, the Integrated Logistics Support ILS can significantly enhance system effectiveness and add value to their competitiveness. Hence, it is not surprising that many organisations outside to the military support the ILS adoption to increase their competence level. Even though the ILS underlying theory is general, there is a lack of suitable methodology that facilitates ILS implementation in other industries such as Oil & Gas industry. In particular when considering complex systems with long life-span, the optimisation of maintenance-related activities is important to fulfil system readiness, safety and whole life cost requirements. Modern petroleum equipment like gas turbines and drilling rigs are dependent on readily available maintenance supports in order to maximise their operational ability. Therefore, it has been identified that the study should be conducted to an effective use of ILS with the petroleum industry. In doing so, the usage of the ILS framework as a decision tool for maintenance optimisation is outlined. This framework embraces ILS concepts to support asset managers in developing their maintenance strategies.

Level of repair analysis and spare parts management have been identified as potential areas for enhancing the use of ILS. In particular, maintenance optimisation is approached as a trade-off between investment in spare parts level and repair capacity. The developed framework delivers cost-effective support strategies obtained with iterative optimisation algorithm built on heuristics and genetic algorithm techniques. Finally, this algorithm has been implemented into computational algorithms. The framework can be employed to identify the optimum level of spare parts and the optimum amount of repair capacity for multi echelon repair network and multi-indenture systems.

The framework has been used to carry out optimisations intended to maximise the availability of gas turbines by varying logistics support parameters. Typical results have shown that a joint optimisation of spare parts and level of repair analysis leads to better results than optimising them separately and emphasises the need for the developed framework. As part of this research, an expert panel validation method has been used to both refine the design of the developed framework and also evaluate its functionality from

experienced practitioners within the Algerian petroleum industry. The results of this validation have demonstrated the advantages of integrating spare part management and level of repair analysis LORA to the problem of maintenance optimisation and shown that the framework is able to deliver optimal maintenance supportability decisions. The generic framework developed in this thesis can be seen a novel and comprehensive model for integrating two ILS elements into the operating tool in a manner that improves maintenance support provision, while remaining both flexible and usable; and therefore as a contribution to a better adoption of ILS technique within Algerian Petroleum Industry.

CHAPTER 1 INTRODUCTION

1.1 BACKGROUND

Historically, system alternative selections were based only on design and development costs. However, after second World War US Defence began to discover that supporting cost during operating period often exceeded two-thirds of the whole cost of acquiring and running complex systems. Additionally it noticed that the increasing needs to develop systems with a desired readiness at lowest costs present a great opportunity to enhance its competitiveness. Consequently, it was argued that the need for cost-effective, highly operational and reliable equipment has compelled to integrate the design, manufacturing and support functions within a same management approach, namely integrated logistic support (ILS). A set of standards and guidelines have been fielded since early 1960s under a US Defence Department to promote and spread ILS techniques throughout the industry. Afterwards, other countries tried to implement this technique by publishing their own standards and guidelines, e.g. The USA MIL-STD -1388-1, (1993) and The UK def standard 00-60, (1996).

Hitherto, equipment has become very complex requiring a very high level of availability to perform their desired functions. At the same time, repair and maintenance actions have shifted towards item or component replacement concept, i.e, when a failure of an item occurs; the defective item is immediately replaced by a new one. Additionally, the defective item reparation may be internal or outsourced by the company. Following this concept, the equipment's availability can be improved significantly while keeping near the operation sites a balanced investment between spare parts and repair capacities. Any company that exploits complex systems notices that a lack of well sustained system with long-term competitiveness and profitability cannot be attained. Then, it becomes clear in most industries that it is insufficient to manage installed systems without an early consideration of support issues, particularly with facing severe competition. As a result, important endeavours have been made to find adequate ways for an efficient implementation of the ILS techniques throughout the industries. After the 1960s, various standards have been published to promote ILS adoption US DOD 4100.35, 1967 and 1968;

US DOD Pamphlet TM38-710, 1972; U.S. MIL-STD-1369-A, 1988; U.S. Army Regulation 700-127, 1999 and 2005; U.S. Department of the Army Pamphlet 700-127, 1989 and US DOD Directive 5000.39, 1980 and 1983).

Given such a crucial part that ILS covers in asset management, there has been a great deal of research in this area. Recently, numerous academic works on ILS and interrelated engineering fields of reliability and maintenance has witnessed the increased interest in the technique. Many various models have been proposed with the primary objective of supporting the diverse functions involved in ILS technique at different phases of a system lifespan. Examples comprise (Jones, 1987; Ebeling, 1996 and Blanchard, 1998), among others.

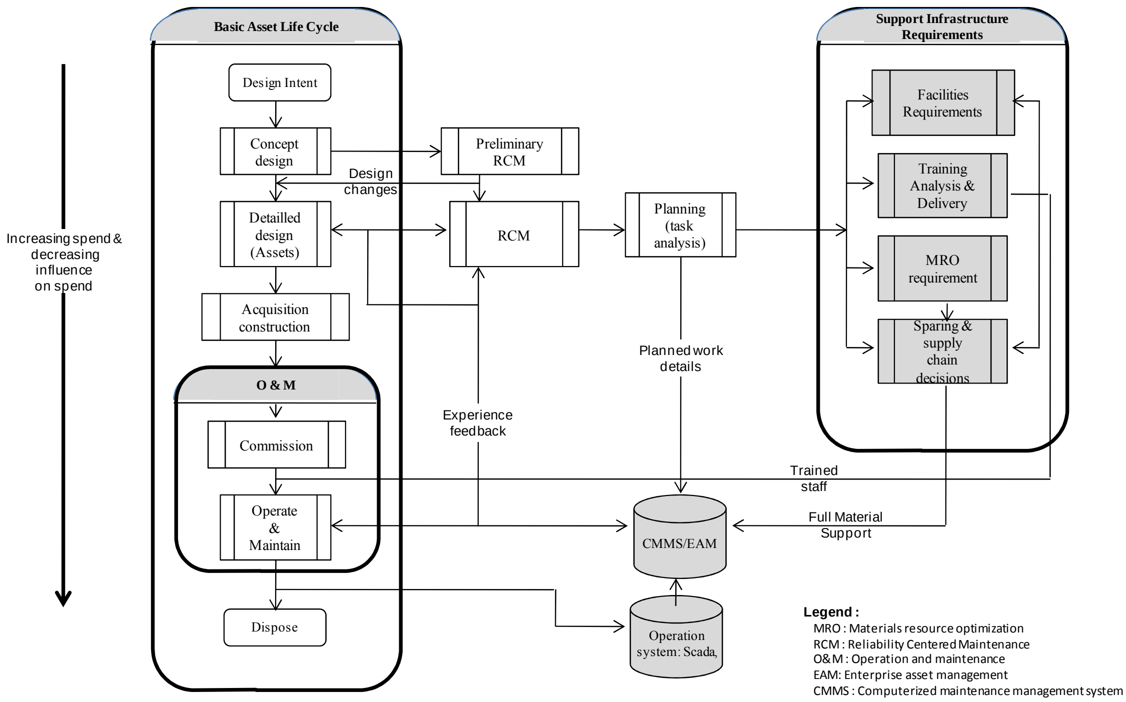

Fig. (1.1): Total Life-Cycle Asset Management (Campbell et al., 2011)

Besides, asset management is a term employed in several fields like finance, economics maintenance, construction, manufacturing and logistics. Within the objectives of this research, asset management refers to the approach to manage all asset life phases to achieve systems ability to meet the operational requirements in a successful way for clients and users (Figure 1.1). Campbell et al. (2011) consider system supportability a crucial aspect in asset management of the complex systems. Therefore, this research will address the effective use of a capital asset in the petroleum sector. The growing complexity of petroleum assets is a phenomenon which involves the financial and physical output of these capital assets. These effects are clearly observable in companies such as the Algerian National Oil Company (SONATRACH). Consequently, there is an increasing interest in approaches which make it possible to maximise the output of these systems and to minimise their whole life costs.

In the following section, level of repair analysis and spare parts inventory control problems are identified within the Integrated Logistics Support (ILS) framework. In Sections 1.3 and 1.4, the relationship between ILS; whole life costing WLC and maintenance is discussed. In section 1.5, the relevant literature on ILS that has recently emerged is critically reviewed with a focus on barriers facing ILS practical implementation. Based on this analysis, the research problem is presented in Section 1.8. Next, in Section 1.9, aim and objectives of the research are set. The research domain is then given in section 1.10. Finally, the structure of the thesis is outlined.

1.2 DEFINITION OF INTEGRATED LOGISTICS SUPPORT ILS

In the last decades systems have become extremely complex leading to more and more interacting maintenance and support activities. It is crucial that companies integrate all aspects of asset management to ensure a high level of their system availability and reliability with regard to a certain harmony in sharing some operational resources. Blanchard (1998) reported that organisations have attempted to integrate their maintenance program development, spare parts logistics and repair capacity installation using their own rules and standards. The US Defence noticed very early (1967) that confusion and a waste of money and resources have been a major attribute to maintenance tasks of the newly introduced equipment within. In order to overcome these pitfalls, they have developed and published a new maintenance concept, called Integrated Logistics Support ILS (US DOD 4100.35, 1967). Several definitions of ILS exist. At its most basic, ILS encompasses the various technical and logistic disciplines to achieve maximum operational availability. In the next chapter the different ILS definitions are investigated, from the military industry, to engineering disciplines and finally focusing on other industry sectors. The military definition, commonly employed in literature, is given in the following subsections.

The US Department of Defence Directive 5000.39 (Blanchard, 1998) defines ILS as:

`Integrated logistics support is a management and technical approach used to influence the support of a designed system in order that the system can be supported at a minimum cost during the utilisation phase of the systems life cycle. '

Another practical definition adopted by several authors (Jones, 1987 and Ebeling, 1996) views ILS:

'as an approach for maintenance planning that defining maintenance concepts and requirements for the system during its life cycle at all levels of maintenance.'

1.3 INTEGRATED LOGISTIC SUPPORT & WHOLE LIFE COSTING

There has been an increasing interest in the use of whole life costing WLC in the field of asset management. For instance, a Joint Industry Project JIP (Vorarat et al., 2000 and Crabb, 1995) within petroleum industry, among others; has been dedicated to better use of WLC. This interest has come up with a common dissatisfaction related to the cost of possessing and using capital assets. The dissatisfaction stems from various reasons such as the budgetary constraints that are facing companies all over the industries, the complexity of today systems, the long term relationship between clients and system constructors and the increasing operational requirements. Similarly, in system design or system acquisition, industry or company directives have suggested the use of whole life costing technique and other related approaches. In such directives, asset managers intensely examine the cost effective decisions inherent to their asset management.

Whole Life Costing (WLC) approach is a tool that creates key metrics for selecting the most cost-effective decision of many engineering problems such as system design, project construction, maintenance strategy and so forth (Kishk et al., 2003 and Blanchard, 1998). Basically, WLC refers to cost analysis and trade studies associated to a system life phases including: preliminary design phase, detailed design and development phase, manufacturing and/or construction phase, operation phase and decommissioning phase (Fabrycky et al., 1991). Some researchers have named a cradle to grave costs determination (Barringer, 2003), where WLC models carry out an investigation into cost breakdown structure to provide a more comprehensive view of costs in the different phases. Despite this need, only a small number of organisations have implemented the WLC technique within their acquisition procedures. Several researchers have asserted that

WLC is mostly conceptual in nature and there is little work about how it is used in practice (Lukka et al., 1996).

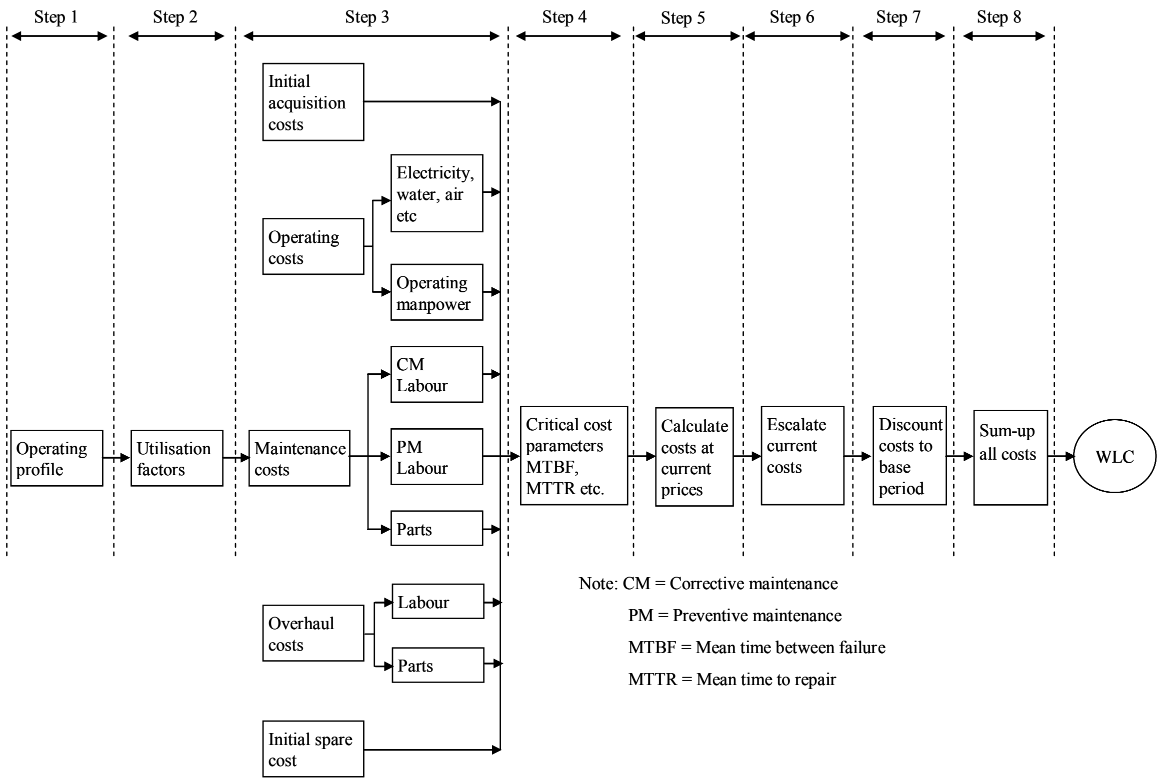

Fig. (1.2): Kaufman's life cycle costing formulation (Woodward, 1997).

One important contributor to system WLC is the cost of maintenance (Kleynera et al., 2008, van der Weide et al., 2010 and Wouters et al. 2005). According to Wouters et al. (2005), the acquisition and maintenance activities are the bulk of system cost. For instance, General Motors spends approximately $3.5 billion annually in which $22.5 million for paying companies to repair failed systems under warranty (Nasser et al., 2002). The same claim is noticed in petroleum industry, where used systems are very costly, not only at the acquisition stage but also at the operation phase. Kawauchi et al. (1999) pointed out that the average ratio between operation cost and the whole life cost for petroleum and gas equipment varies from 60 to 80%. For instance, a gas turbine sold at a purchase cost of $10 million, its whole life cost for a period of 20 years and 15% discount rate is about $ 44.3 million. The contribution of purchase cost in whole life cost is only 23% (Riberio et al. 1995). Therefore, decisions based only on the initial acquisition cost alone are unsatisfactory; some considerations must therefore be given to subsequent costs which will accrue throughout the equipment life. As a result, this witnesses the significance of the use of WLC technique for monitoring this equipment; where initial and future costs are both considered in WLC decisions. Kaufman (1970) has emphasised the importance of cost categorisation and especially for operation and maintenance costs which should split further into their elemental components. Spare part and repair cost are considered as the major cost elements of maintenance and the main contributors to whole life cost. Therefore, maintenance cost optimisation should be an important contributor to be considered to achieve significant WLC reduction.

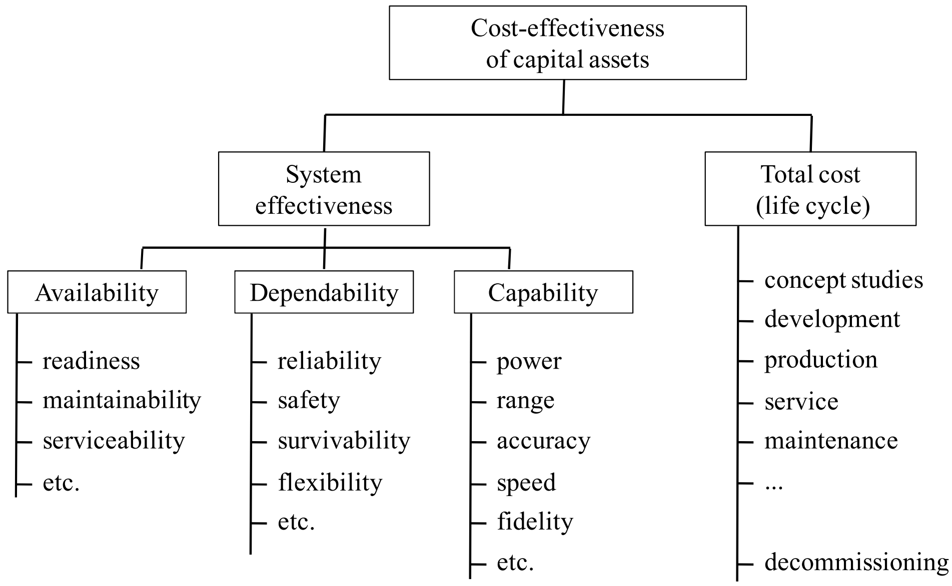

Fig. (1.3): Cost-effectiveness structure according to Juran (1988).

In the area of maintenance optimisation, many researchers have noticed that integrated logistic support (ILS) approach may cut maintenance and logistics support costs for a system up to 50% (Tysseland, 2008). In the context of ILS, the whole life costing is also considered as a key parameter in selecting the most effective design alternative. According to Juran (1988), cost-effectiveness is the balance between system effectiveness measured generally by RAMS (reliability, availability, maintainability and supportability) and the whole life cost, as illustrated in figure (1.3).

Therefore, integrated logistic support is viewed as a management technique to guarantee that the installed asset fulfils the expectation and requests of the clients during all over the asset life cycles. This achievement is not only related to operational efficiency, but also related to cost effectiveness concerns (Blanchard, 2004). Therefore, maintenance-related solutions, e.g. maintenance optimisation, should be approached from a whole life cycle and logistic perspective. To sum up, benefits of ILS for WLC implementation may encompass: meeting asset operation requirements, increased asset availability, clear visibility of maintenance and support costs and detailed cost structure (IEC, 2001, Ruiz-Torres et al., 2010).

1.4 MAINTENANCE AND MAINTENANCE SUPPORT

Traditionally, maintenance and its related support activities have been regarded as non-productive function (Nikolopoulos et al., 2003). Nevertheless, nowadays, it is asserted that many organisations are shifting towards strategies where maintenance may add value to their business. Systems are necessary to company's activities, their malfunction should be minimised. Since maintenance contributes more than 60% of the whole life cost (WLC) of physical systems, companies have shifted from maintenance and its related strategies as nonproduction function towards strategies where it is considered as a center of investment adding values to their business (Ostebo, 1993). System downtime is usually made up of the two main categories: diagnosis and repair time and repair waiting time triggered by unavailability of the needed resources. Therefore, system availability is directly influenced by repair delay in the case of corrective maintenance or preventive maintenance (Gits, 1992 and Moubray, 1997).

On the other hand, companies prefer maintaining items of the system rather than the system itself to reduce the spent time on maintenance activities (Keebom et al., 2010, Muckstadt, 2005). When maintenance actions are carried out, subsystems or components requesting repair are removed and replaced by RFU (Ready-For-Use) items. The removed items are either scrapped or sent to repair. This strategy is called repair by replacement and for which the optimisation of the spare part inventory and repair capacity is a paramount task for asset managers (Muckstadt, 2005). Asset managers are continuously compelled to find the optimal balance between spare parts availability, repair capacity and operational budgets during life-span of their systems. There is therefore a necessity to develop models to minimise maintenance costs throughout system life.

In addition, the petroleum environment is an aggressive environment where systems often suffer significant wear and tear. This makes cost-effectiveness difficult to attain. Hence, a reliable and well-structured logistics support organisation is crucial to ensure satisfactory system operations. The environment of the petroleum industry, similar to the Algerian Petroleum industry, is characterised by:

- *a wide range of operational requirements;*
- *Relatively complex Petroleum systems;*
- *System operating generally in different remote and desert areas;*
- *High failure rate of components;*

1.5 INTEGRATED LOGISTICS SUPPORT ELEMENTS

Integrated Logistic Support (ILS), adopted as an engineering discipline, aims to guarantee that the support resources are available in satisfactory quantities and in place easy to obtain when needed. In military sector, standards have provided a prescribed ILS process to achieve adequate support solutions. Many authors (Galetto, 2010; Sleptencko et al., 2005 and de Smidt-Destombes et al., 2007) have reported that the two significant ILS elements should be considered not only when acquiring or manufacturing systems but also during all system life cycle are: allocating repair capacity among repair network (namely level of repair analysis LORA) and allocating spare parts to stock sites to support system operations (Blanchard, 1998 and Jones, 1987). These elements are referred to as Multi-echelons Multi-indentures repair and spare part management, that haves been widely considered by researchers and practitioners. Literature also discusses the limited academic research with regard to these ILS elements (Basten, 2009). In such a case, support lead time is constituted of service part time, repair time under limited capacity and operational requirements which is frequently changing with regard to operational environment. Consequently, Multi-echelon Multi-indenture repair and spare part management intend to deliver over system lifespan optimal solutions where a reduction of the reparation costs and time is balanced against system availability requirement.

1.5.1 LEVEL OF REPAIR ANALYSIS LORA

Level of Repair Analysis, LORA, is an analytic process to evaluate the cost of repair capacity allocation options, by examining spare parts stocking policy, manpower and support equipment cost (Blanchard, 1998; Basten et al., 2008; Baros, 1998 and Baros, 2001). For a complex equipment encompassing generally thousands of parts and items, structured into a number of levels of indenture and with several feasible repair decisions, LORA intends to optimise repair and maintenance costs all over system life cycle. Maintenance task complexity, manpower skills-level requirements, special repair facility needs, item reliability and maintainability, item supply chain and economic criteria are the underlining factors for the selection of repair options.

The primary objective of Level of Repair Analysis (LORA) is the selection of the most economical maintenance strategy for any components of the system. This selection is based on criteria taking into account the optimal maintenance facility that composes a repair network, the required capacity of each facility and the efficient repair decisions, i.e., to determine the location where discard or repair will be performed (Blanchard, 1998 and Jones, 1987; Basten, 2009 and Baros, 2001).

1.5.2 SPARE PARTS INVENTORY ANALYSIS

Many of today's systems, such as nuclear power plants, aircrafts, Oil & Gas installation, military and advanced medical equipment require a high level availability. As a result, sufficient maintenance resources which play an important role in system operation management are required. One strategy to satisfy the required operational availability is to possess sufficient spare parts to ensure immediate replacement of worn out items. The major dilemma that faces logistics planners is which amount of spare part to possess. A very high inventory levels which ties up large holding costs maintain system availability very high on the one hand, whereas on the other hand small number of spare parts may result in poor maintenance service or extremely costly reparation actions. To guarantee an efficient continuity of operations, a specific level of inventory must be maintained. However, this must be traded off with the cost of spares and part obsolescence system availability (Li et al., 2007; Buré et al., 2010; Rezg et al., 2008 ; Liao et al., 2010 and Liang et al., 2011).

Models based on multi-item approach have been considered by researchers. As an example, Sherbrooke (1968), introduced METRIC, a mathematical model for a multi-item two-echelon structure with one central warehouse and multiple local warehouses (Multi-Echelon Technique for Recoverable Item Control). His optimisation algorithm maximise objective function, generally the overall system availability, using greedy method that distributes a given budget over the items. Spare part management has become the line of research that has been deeply considered by various researchers (Muckstadt, 1973; Slay, 1984; Graves, 1985; Diaz, 1997; Avzar et al., 2000; Kennedy et al., 2002; Rustenburg et al., 2001; Kim et al., 2005; Lau, 2004; Alfredsson, 1999 and Karin, 2009) among others. Whereas there is a great amount of literature on inventory management, relatively little has been considered on the interaction between spares and repair capacity (Dinesh Kumar et al., 2000). Only a few of the current literature has dealt with the combination of these two support elements in a specific situation.

1.6 INTEGRATED LOGISTICS SUPPORT IMPLEMENTATION

Integrated logistics support is a structured approach to predict all maintenance needs for installed systems. Developed by the military sector in 1960, supported by the aviation industry and applied maritime and construction industries ILS is nowadays being adopted in almost any industrial sector. In addition to suggesting the anticipation of support activities, ILS provides an integral model to maintenance optimisation as well. In the last decades, a number of practical ILS models have been proposed. The main feature of these models is that each of them is developed to suit the characteristics of one or two industries and no common model exists. Consequently, the ILS models should be adapted accordingly. ILS practitioners have developed a poor reputation and, indeed, the process has fallen out of favour for a significant number of manufacturers.

Although it is commonly argued that most ILS elements are well developed in theory, their adoption by industry has received less attention. Various research works have dealt with spare part management, repair and maintenance optimisation; whereas little has been published on the interaction between maintenance, spares and repair. Most of the current literature focuses on one of these ILS aspects dealing with the interaction of two out of these three components in specific settings. According to (Karin, 2009), sufficient models exist to satisfy the needs of ILS but additional effort is required to streamline the use of these models and make them more accessible to potential users.

1.7 JOINT PROBLEM OF LORA AND SPARE PART INVENTORY MANAGEMENT

Recently, many models have been proposed to assess the two ILS elements cited previously and mainly for spare pare optimisation. This thesis will address spare part allocation by considering repair shop capacity. The focus on both spare part allocation and Level of Repair Analysis, particularly considered within defence sector, will be investigated for practical implementation within the Algerian petroleum industry. Recent trend analysis showed that spare part allocation for multi-indenture systems and multi-echelon repair structure must deal with repair capacity allocation. The available techniques do not address all these issues adequately. Moreover, repair analysis and spare part allocation are often solved independently, as discussed in Section 1.2. Companies usually solve spare part allocation explicitly using available optimisation models after setting the structure of repair shops by either maintenance expert judgement or equipment supplier advice. Besides, spreadsheets are used to assess what level repair costs by running few scenarios only for most costly components. Obviously, this does not guarantee the optimal solution and it is time consuming when the number of parts is high.

In this situation, the reasonable choice for any company is to focus on maintenance support according to the required system availability. Nowadays, companies increasingly seek for system upkeep with a given target availability at lowest costs. Therefore, system managers need tools to estimate maintenance and support costs. Besides, those costs should be optimised with respect to system availability and company budgets. System availability can, hence, be balanced against support costs (e.g., spare part cost, repair costs and other maintenance costs).

Researchers have asserted that spare part inventory and repair capacity are essential elements in an overall maintenance concept (Dinesh Kumar et al., 2000). Only few papers have proposed quantitative models integrating these elements. The well-known spare part models are the models based on METRIC (Sherbrooke, 1992). Even though METRIC is based on the assumption that the capacity to repair parts is infinite, further developments have been done to include finite repair capacities. Different methods have been considered, such as: queuing networks, Markov chains and using appropriate finite capacity queues (Albright et al., 1993; Zijm et al., 2003; Sleptchenko et al., 2002 and Gross et al., 1983).

Eventually, few researcher works dealt with the simultaneous optimisation of spare parts and repair capacity have been published. Ebeling (1991) developed a single echelon multi-item model where each item has its own resource capacity. A more general trade-off between repair capacity and spare part inventories has been proposed by Sleptchenko (Sleptchenko et al., 2003). Their model is different from this research focus, because they estimated only spare part with respect to installed repair capacity by using queuing network and they did not integrate costs of the installed repair capacity under their optimisation algorithm. From this perspective, the goal of this thesis is to develop a tool to solve inventory models that reflect the real relation between inventory holding, repair structure and repair capacity and level of repair. The contribution of this thesis to the existing models from the literature is twofold: (1) a tool that optimises both spare part inventory and level of repair analysis under finite repair capacity, and (2) a tool that fits the requirements of petroleum system management.

1.8 PROBLEM STATEMENT

The above state of the art of ILS as a maintenance optimisation approach may be considered as less than satisfactory. In practice, the LORA problems and spare parts inventory are often solved separately, as mentioned in Section 1.5. Besides, the available models are too restrictive to be adopted in practice. They usually assume one-indenture level and a two-echelon level. These features have limited the motivation of practitioners and asset managers in implementing ILS approach to support systems for modern industries and especially in petroleum industry. In addition, the most installed systems that require ILS, such as petroleum industry, can be:

- Identical complex systems operating throughout large areas;
- Systems with thousands of subsystems and components;
- Systems that share a number of repair facilities.

The research problem can be therefore expressed as follows: there is no an integrated framework available for the development of an ILS approach for a petroleum installed systems. A need remains for developing and combining the two models namely LORA problems and spare parts inventory designed to suit the operation and maintenance requirements. In addition, these models should be accepted by practitioners by ensuring the speed and ease of use. Consequently, they should be implemented in the form of computer algorithms. Then, these algorithms can be incorporated into a well-structured framework.

1.9 AIM AND OBJECTIVES

1.9.1 AIM

The overall aim of the research work that underpins this thesis is to develop a maintenance optimisation model suitable for the oil & gas industries. The model will be used to optimise maintenance supports based on an integrated model of level of repair analysis and spare parts stocking for complex systems. The case study of this research will be some physical systems employed by the Algerian National Oil Company (SONATRACH).

1.9.2 OBJECTIVES

The objectives logically contribute to achieving the overall aim are:

- Undertake an extensive literature review to understand basic ILS requirements and to identify gaps where ILS implementation should be improved.
- Outline a theoretical framework for major ILS elements.
- Investigate the influence of the different ILS elements on maintenance efficiency.
- Develop a methodology, based on the use of LORA and spare part model, capable of optimising maintenance activities.
- Derive suitable models suitable for petroleum industry
- Combine the above models to form an integrated ILS tool.
- Validate the developed tool real world applications and comparing the results with other methods proposed in the literature.
- Validate the developed tool through a series of tests.

1.10 RESEARCH DOMAIN

In the previous sections, integrated logistics support ILS has been discussed in relation to whole life costing WLC and maintenance optimisation of physical systems. The major driving force for optimising maintenance arises from the competitive environment in which companies perform their business and system complexity. For this reason, it is worth introducing ILS elements within maintenance strategies for cost savings and client satisfaction. To limit the research domain, the following three-level approach is considered:

- Petroleum Asset Management
- Maintenance supportability
- Maintenance support Optimisation

With respect to system monitoring, RAMS (reliability, availability, maintainability and supportability) concepts consider all the issue that maximise system efficiency over its useful life (Murty, 1995). Reliability and maintainability concepts are largely used at the conception and design phase of systems, whereas the availability and supportability concepts are mainly employed during operation and decommissioning phases. Considering system availability, the focus of this research has been on maintenance optimisation through support optimisation ignoring to consider reliability and maintainability performances because the maintenance efficiency is influenced by the maintenance organisation and its support resources, particularly spare part provision and repair capacity. The reliability and maintainability features are considered as characteristics of the technical system itself.

From whole life cycle point of view, maintenance activities have the largest effect on the system total cost. The analysis of maintenance costs is limited to the cost of repair shops and spare part, and the other cost sources are not considered. Besides, the study output is a framework based on ILS technique for the maintenance optimisation. For these reasons, this research work will not consider all ILS elements but it focuses only on the interaction between spare part provision and level of repair analysis.

Regarding the application area, this research focuses on complex systems. A further limitation is petroleum systems, since the research sponsor is the Algerian Oil & Gas national company. Besides, petroleum industry is a type of sector where systems are technically complex and have long life cycles.

1.11 LAYOUT OF THE THESIS

The outline of the thesis is as follows. A detailed review of pertinent literature is discussed in the next three chapters. The basic concepts and approaches of ILS are critically reviewed with emphasis on the role of ILS as maintenance optimisation tool in chapter 2. Chapter 3 present a discussion on Level of Repair Analysis model. Spare parts management, their properties and their use in practice are outlined in chapter 4. Chapter 5 deals with the design of research methodology. Chapters 6 and 7 cover the case studies. Chapter 6 deals with Level of Repair Analysis example and Chapter 7 discuss the optimisation of spare part inventory. In chapter 8, the developed models are extended to allow simultaneous optimisation for both level of repair analysis and spare part inventory. Besides, other essential features of the developed models are illustrated through additional applications. In chapter 9, the validation of tool is carried out. The research work is summarised, the conclusions are drawn, and the directions for further future research are introduced in chapter 10.

CHAPTER 2 INTEGRATED LOGISTICS SUPPORT ILS A LITERATURE REVIEW

2.1 INTRODUCTION

In the previous chapter, integrated logistics support (ILS) was introduced. It has put forward practical ILS technique limitations and the study problem statement, and included a discussion of the research importance. This chapter intends to investigate the technique deeply through a critical review of basic concepts and elements of ILS. This has been carried out to identify practical ILS difficulties to deliver an efficient tool for system readiness within the petroleum industry.

In the following section, a historical background of ILS and its available literature are briefly introduced. The major finding of this review is the lack of academic literature about ILS, which is mainly based on military guidelines and standards. Various existing ILS models are critically reviewed in Sec. 2.5, with a particular focus on its logistic support analysis (LSA). Then, ILS elements as described in the standards are reviewed. This is followed by a discussion of the joint LORA and spare part optimisation problem in Sec 2.6. Finally, the main findings of the chapter are summarised.

2.2 BACKGROUND

In an increasingly competitive environment, organisations are always striving to find out management approaches to meet system operation needs. It has been noticed that these needs rely on the integration of system development and operation functions within asset management tools (Fabrycky, et al., 1991; Ballou, 1985; Markeset, et al., 2001 and Goffin, 1999). The emphasis is to balance the whole life cycle costs and alternatives to support system operations for all procurement programs. Supportability is becoming progressively more requested because of the alarmingly high maintenance and operation costs of systems. In the current environment of tough competition, this will become even more imperative. Several practitioners (Blanchard, et al., 1998; Markeset, et al., 2003 and Kennedy, et al., 2002) have revealed that the supportability costs can present a large amount of a system's whole life cycle cost. Within military industry, this amount can reach 80% of the whole system life costs. For example, system maintenance and operation cost over $300 billion annually to the U.S. industry, in which the U.S. military industry spending is around $79 billion. Therefore, some of the objectives for using supportability principles are to reduce whole life cost through reliability and maintainability of systems and the development of the related resources required system maintenance and operation.

Maintenance and support managers are experiencing ever-increasing operation requirements to enhance system availability and decrease whole life costing (WLC). Maintenance, inventory parts and repair of complex systems have received significant consideration in the last decades, due to the high level of requested availability and increasing capital cost invested in maintenance facilities (El-Haram, et al., 2003; Rustenburg, et al., 2001 and Moynihan, et al., 1995). A great consideration has been given especially to identify optimal maintenance strategies, trade-off the costs of maintenance actions and the costs of malfunctioning and system downtime. This need for cost-effective and highly functional systems is placing asset manager under a big pressure for more integrated decisions including all aspects of operation phase. Furthermore, organisations notice that this pressure intended to design systems compatible with reliability, availability, maintainability and supportability concepts to reinforce their market competitiveness.

In addition, actual technical systems including airplanes, petroleum apparatus, military equipment and naval vessels among others are becoming more complex and requiring at the same time a high level of availability. The latter can be enhanced in different ways. System uptime is maximised by redundancy of critical items that leads to more expensive system acquisition costs (Kennedy, et al. 2002 and Blanchard, et al., 1995). Another way to reach a high system uptime depends on efficient support and maintenance policies. To this end, integrated logistics support technique (ILS) offers a competitive advantage for companies in terms of whole life cost minimisation. This technique encompasses various elements namely: maintenance, reliability, manpower, support and test equipment, repair facilities, training devices, packaging, handling, storage transportation, technical data and documentation. Since system availability could be enhanced by either maintenance activity or by reliability improvement based on the redundancy, a question that arises as to what is more efficient. This means, the designer selects a system with several redundant items and less maintenance costs or vice versa. The well-balanced compromise should minimise the whole life cost of the system.

On the other hand, the above systems are generally operating in disperse areas associated with distribution repair activities (Rustenburg, et al., 2001). To achieve efficient maintenance tasks, repair facilities should be categorised it as a hierarchically structure ensuring an immediate response to system failure whenever is operating. As a result, the most cost-efficient tasks are based on optimal distribution of support resources at all repair locations (e.g. central and remove repair shops). An integrated approach to maintenance planning is necessary due to the inherent trade-offs involved in support resources. Examples of such trade-offs include repair capacity, spare part inventory cost, operation budget and system availability (Gustin, et al., 1995). Consequently, a growing necessity exists for integrated support technique especially where aspects such as performance, maintenance support and whole life cycle cost (WLC) are concerned. This technique is of greatest importance in system design phase and system operation, since 70% of system properties and costs are defined and easily changed in design period and more than 80% of system whole costs are incurred in operation period (Blanchard, 1998).

As stated above, technical systems have becoming recently more and more complex. Similarly, the strategies of providing support for system operation also have become more involved. Blanchard (1998) and Jones (1987) argued that in the US military industry, usually, there were no common maintenance programs throughout individual military organisations. Moreover, each of these organisations was responsible for its own maintenance program according to its own guidelines, which were generally different from those in other organisations. As a result, there was confusion to maintain newly introduced systems across organisations. Another difficulty that the military industry has experienced is the growing maintenance costs of the traditional approach. Even though profit is not the common purpose of these organisations, mastering their costs and maximising the availability of their systems started to become a requirement in their asset management policy. In order to overcome these hurdles, the US defence department introduced in 1960's a new management technique, namely Integrated Logistics Support ILS (US DOD, 1983). Its Fundamental objective is to develop, plan and direct activities based on logistics support requirements for military equipment. Although initiated by the military industry, ILS rapidly spread through other industries. ILS is used to develop maintenance strategies for aviation, maritime, railways transport and power plants. Hitherto, ILS has been viewed as a solution to maintenance optimisation in capitally intensive industries (John, et al. 2005; El-Haram, et al., 2003; Moss, et al.; 1985; Moynihan, et al.; 1995 and Rustenburg, et al., 2001).

2.3 MAINTENANCE OPTIMISATION

Systems Reliability Centre (2003) defines maintenance optimisation as a maintenance strategy that is appropriate to:

"…balance the maintenance requirements (legislative, economic, technical, etc.) and the resources used to carry out the maintenance program (people, spares, consumables, equipment, facilities, etc."

As discussed previously, many physical assets have become more complicated and more large-scale. Their operation relies heavily on the maintenance of such systems. Consequently maintenance strategies have been developed to generate maintenance plans with the following alternatives: proactive maintenance (preventive and condition based maintenance) and reactive maintenance. These strategies are one of the most crucial topics in system operation since the system can be costly in addition to any negative consequences of system downtime. In preventive replacement, the items are replaced before they fail. In corrective maintenance only the failed items are replaced. Besides, condition based maintenance is carried out according to the condition performance of an item or component as revelled by condition monitoring processes (Moubray 1991). A large number of maintenance models have been developed to find the most advantageous balance between different maintenance strategies have been examined by several authors (Arthur, 2005; Dekker, 1996; Dekker, et al., 1997; Sandve, et al., 1999; Boschian, et al., 2009 ; Ghosh, et al., 2009 and Samrout, et al., 2009). For instance, a comprehensive review of maintenance models is listed in (Dey, 2004; Khan et al., 2003a, 2003b; Montgomery et al., 2002 and Willcocks et al., 2000). The well known optimisation policies include age replacement policy, random age replacement policy, block replacement policy, failure limit policy, repair cost limit policy, repair time limit policy, etc (Besnard et al., 2010; Besnard et al., 2011; Fiori de Castro et al., 2006; Goti et al., 2006; Sánchez et al., 2006; Selvik, et al., 2011; Vasili et al., 2011; Zewei et al., 2010 and Zieda et al., 2011). Every kind of these policies has different features, advantages, limitations, and relationship with others. However, these models are questionable in practice. They are based on the assumption that failed items are replaced instantaneously; i. e., spare parts are available whenever they are needed. Sufficiently large number of parts should be kept in hand, and as a result, inventory costs will be very high. From a supportability viewpoint, the maintenance optimisation is intended to increase system availability by immediate support responses. Smith et al., (1996) asserted that supportability issues have mostly been ignored by designers even though they represent a large proportion of the whole life costs associated with a system maintenance and operation. To overcome the above limitations, a supportability optimisation technique that enables the consideration of all principal support elements and in particular those related to repair and spare inventory, will play an important role for maintenance effectiveness. In supportability concept, system performance is mainly measured by the operational availability, A, determined by the following formula (Blanchard, 1998):

$$\mathrm{A} = \frac{\mathrm{MTTF}}{\mathrm{MTTF} + \mathrm{MTTR} + \mathrm{MTTS}} \tag{2.1}$$

Where:

MTTF: mean time to failure

MTTR: mean time to repair

MTTS: mean time to support

Maximising A requires a balance between the inherent reliability and maintainability characteristics and support considerations with respect to the whole life cost (Sherif et al., 1996). It appears from equation (2.1) that the smaller MTTR and MTTS are, the higher A is. Therefore, integrating supportability issues into maintenance optimisation is crucial in order to achieve a cost-effective use of systems. Besides, supportability is also deeply influenced by logistics considerations such as installed repair capacity, spare parts, personnel, maintenance tools,... etc, which are client dependent. Hence, given that reliability and maintainability features are fully set during design phase, the supportability is usually regarded as the characteristic of operation phase on which system owners can achieve the most cost reduction.

2.3.1 MAINTENANCE STRATEGIES

As indicated above, maintenance can be defined as spectrum of technological, technical, economic and organisational actions to restore the system to its operational state after a failure. There are various maintenance strategies: preventive, corrective and condition based maintenance as shown in Figure 2.1. (Nowlan et, al., 1978; Gits, 1992 and Moubray, 1997)

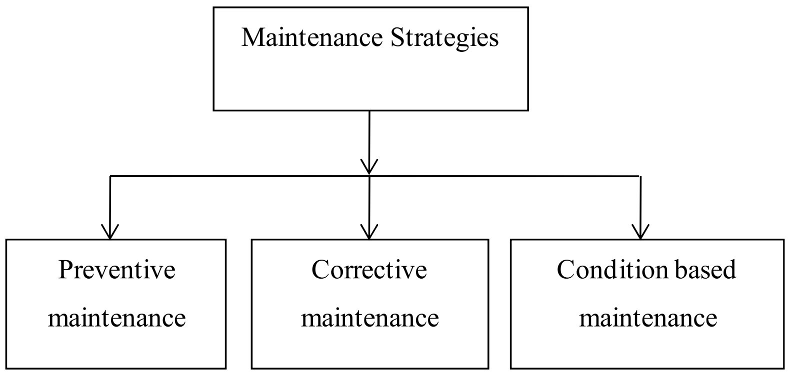

Fig. (2.1): Classification of Maintenance Strategies

Corrective maintenance entails reactive actions to correct faults. Preventive maintenance, on the other hand, involves proactive tasks to avoid possible future problems. Condition-based maintenance strategy is carried out based on the condition of the system being inspected. This implies the monitoring of one or more parameters describing the wear process (e.g. lubrications, vibrations, cracks, etc…). The selection of an effective maintenance strategy is an essential topic in practice as it directly influences system operation. However, all these strategies are cost-effective according to support reaction. In fact, a great part of the maintenance whole life cost stems from the organisation support function. Therefore, maintenance strategies which greatly affect both the system availability and its WLC, have to be identified based on supportability characteristics (Blanchard et al., 1995). As a result, the prompt and safe coordination of supportability elements within allowed time is a vital aspect for the maintenance efficiency. Missing maintenance resources are mentioned as the principal cause for maintenance delay. Since spare parts are often costly, this delay cannot be minimised simply by increasing inventory stock. Through a joint optimisation of support elements, maintenance tasks can be efficient to support maximum system availability with minimum maintenance costs.

2.3.2 WHOLE LIFE COSTING

One of the basic problems within maintenance is to decide between different maintenance strategies, repair, discard and replace alternatives. Faced with budget constraints, asset managers generally select their decisions according to operation requirements and costs. Degraeve et al. (1999) and Plank et al. (2002) have argued that the most cost-effective decisions are those based on whole life costing WLC. WLC models typically optimise maintenance costs as a function of fixed capital cost and annual variable costs. The fixed costs include mainly repair facility costs. However variable costs consist of material, manpower and spare parts related to maintenance tasks. These costs largely depend on the failure rate of system items. WLC optimisation model are intended to minimise costs by the identification of the number of repair facilities to be installed and assign subsystems or components to these so that the whole cost is minimised. Another reason for WLC use in maintenance management is operation phase length. For capital systems, this phase is usually the longest one; it can vary from a couple of years to more than 30 years (e.g., for petroleum assets). Consequently, the proportion of the WLC associated with maintenance and its support activities during the operation phase is quite large:

- More than 75% of WLC costs of physical systems are made during the operation phase (Gupta, 1983 and Saranga et al., 2006).
- 30-50% of WLC are made up of corrective and preventive maintenance costs (Basten, 2006; Franssen, 2006 and Meutstege, 2007).

In addition, Blanchard (1992) has asserted that WLC is one of major parameter to consider in evaluating cost-effectiveness of any system. The other parameters (reliability, maintainability and availability) are categorised into two groups: (1) intrinsic parameters of system effectiveness which determine WLC implicitly (e.g. reliability, maintainability and availability) and (2) extrinsic parameters (i.e. client induced availability) which influence

WLC of system operation phase. The second group is influenced by repair facilities, supply support, manpower and training, etc.

2.4 DEFINITIONS OF INTEGRATED LOGISTICS SUPPORT

Integrated logistics support (ILS) is a comprehensive and structured technique that maximises system performances with the lowest whole life support costs. ILS is defines as (US DOD, 1983; United Kingdom Ministry of Defence, 1996; Blanchard, et al., 1995; Blanchard, 1998 and Jones, 1987; ISO/IEC 15288, 2002 and Rutner, et al.; 2001):

"disciplined and unified management which guarantees that the most appropriate means of the highest quality are in the sufficient quantity, at the exact place, at the correct time to support equipment throughout its intended life cycle at the minimum cost"

Integrated logistics support (ILS) presents the following benefits to organisations:

- System design could be enhanced by integrating reliability, maintainability, testability and supportability.
- ILS process, which underpins system supportability engineering, must be effective and cost-effective through life system support.
- The ILS process should lead to the optimum support solution.

The meaning of the expression "INTEGRATED" is twofold. First, it refers to a spectrum of disciplines relevant to the field of decision support as whole life costing, management, safety and supportability (Figure 2-2). The ILS approach tries to combine all of these disciplines to support systems at a desired level of operational efficiency and under realistic and acceptable whole life cycle costs.

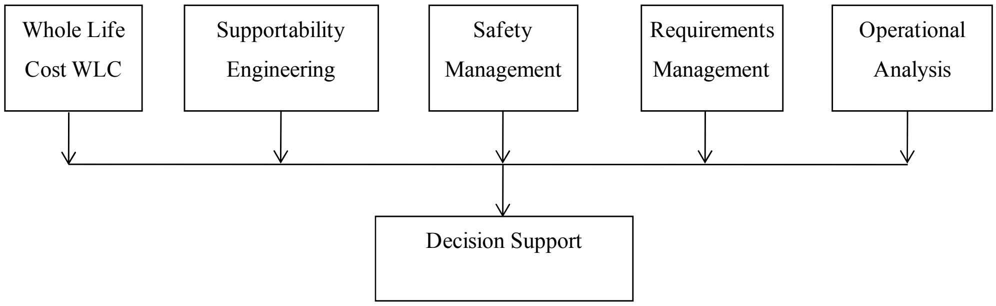

Fig. (2.2): System support disciplines (Blanchard, 1998)

Second, the expression "INTEGRATED" also refers to the contribution of logistics support at all life cycle phases. The life cycle of any system can include six (06) different phases (Blanchard, 1998 and Jones, 1987). Figure (2-3) shows schematically a six-step ILS process described in (United Kingdom Ministry of Defence, 1996 and United States Department of Defence, 1983). During the design phase the logistics engineers should identify their view of the system supportability policy. Often these early ILS considerations are vaguely defined but they represent a guide to final ILS plan solution. In the final steps, the potential support solution, called ILS Plan, has to be set on the basis of cost-effectiveness within a support strategy.

- In the concept formulation period, the need for new systems is expressed as solution to the situation where the installed systems are either too expensive to exploit or do not fully accomplish their designed mission. The design objective is a system that will achieve the expected performance level satisfying the operation while limiting whole cost to a tolerable level. At this time, ILS draft is to define the mission profile and identify vaguely the required resources to support this new need.
- In the feasibility study period, different options to fulfil this new need are considered. The utmost objective of this period is the identification of the most practical options for additional examination. At this stage, ILS selects the most efficient support alternatives and the most suitable to the identified options. The proposed support alternatives are generally based on benchmarks and on feedback from installed systems. The ILS technique includes engineering and economical optimisation methods where the major aim is to identify and select the option that generates the highest system performance with the lowest life cycle cost. To attain the best system

performances including analysis whole life cost, ILS should be performed in the early design stages.

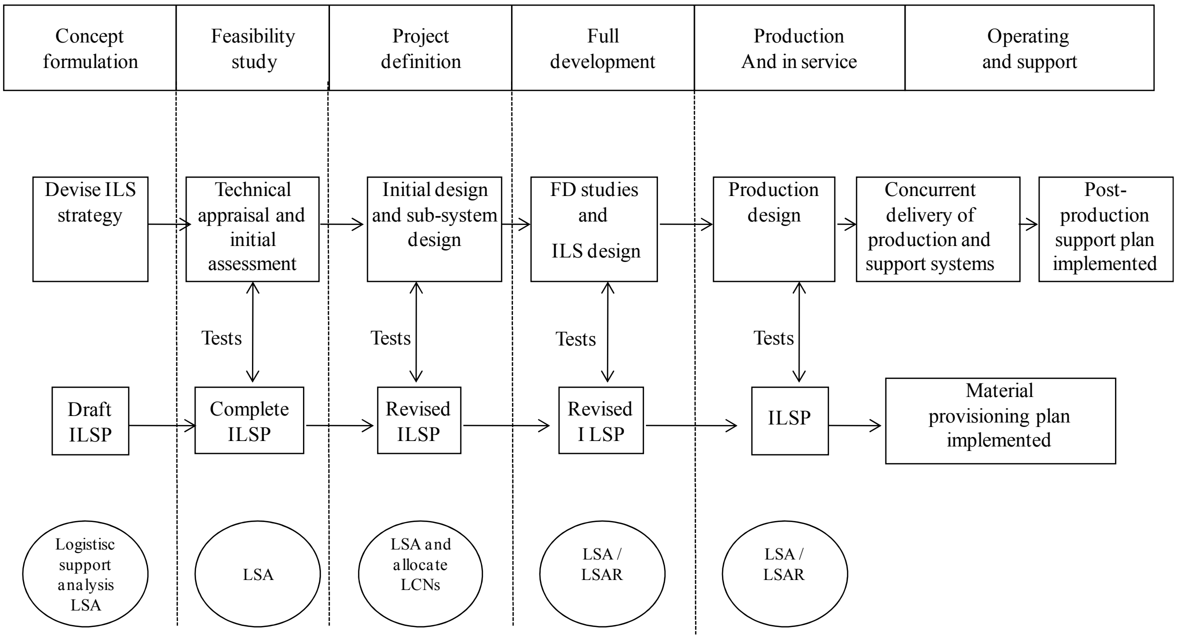

Fig. (2.3): ILS process trough system life cycles (US Department of Defence, 1983)

- In the project definition period, a prototype of the selected option goes through a detailed engineering process to meet all the requirements at affordable costs. A key aspect of this period is the identification of a satisfactory support package. This encompasses logistics programs, spare parts inventory, maintenance policies, repair capacity, training courses, etc. As a result, detailed ILS programs are studied in collaboration with manufacturing, operating and maintenance parties. The ease of change in ILS design declines quickly as the system design advances in time.
- In the full development period (production and in service periods), the systems are produced with their support package. The logistics engineers should have 95% complete of the support solution.
- In the operation period, the systems operate in their intended setting and their ability to accomplish the needs is assessed continuously. At the end of the operation, two options are considered: systems are either sold to other organisations or dismantled. These decisions depend on the systems performance, operation budget and costs; and the utility of these systems. Usually before disposal actions, a need for new systems is identified and,

therefore, a new life cycle starts.

ILS has become a well-known technique for studying equipment designs prior to their manufacturing in military industry. However, the literature reports a limited use of ILS in other industries (John, et al. 2005; El-Haram, et al., 2003; Moss, et al.; 1985; Moynihan, et al.; 1995 and Rustenburg, et al., 2001). One of the main reasons for this limitation is a lack of unified techniques to assist companies with the acquisition processes. Another barrier to practical adoption of ILS is the fact that Original Equipment Manufacturers (OEMs) are not the companies which use and operate the systems. Therefore, the loop between design phase and exploitation phase is no longer coupled. Item failure, repair and replacement rates are generally based on manufacturer catalogue while system operating environment is slightly considered in maintenance strategies (Oner, et al., 2007).

Often, logistics support can be split into two missions: services to support systems and services to support clients when OEMs are not system users. The first part of services encompasses ordinary and basic after-sales service including: maintenance expert assistance, spare part, etc. This type of service is directly related to reliability, maintainability and availability of the product. The second part covers the issues that permit the clients to maximise outputs from the purchased product. It consists of advanced training of personnel, analysis of support and maintenance policies and enhancing system performance during operation phase. Even though these services guarantee long-term revenue to manufacturers, the client satisfaction and fidelity is also an important approach to develop. Consequently, OEMs find themselves providing more services at lowest whole cost related to system operation, maintenance, modifications, and improvement, etc. Kim et al. (2007) pointed out that the OEMs services can be classified into two categories: service agreements and Performance Based Logistics (PBL) agreement. The first one covers mainly material services by providing labour, spare parts and other support resources; however for the second one the OEM is responsible a service level generally with respect to the system availability at the client location. Furthermore, there is a large motivation nowadays in Performance Based Logistics (PBL) agreements since the main objective for the clients is the availability of their systems rather than possessing support resources. Consequently, PBL agreements are becoming more frequent and OEMs are compelled to develop tools optimising system availability.

2.5 ILS MILITARY GUIDELINES AND STANDARDS

Integrated logistics support (ILS) aims to assist in designing or acquiring military systems that meet the field requirements while ensuring the best value for investment money. The most universal guidelines and standards have been US Mil-Std 1388-1A and Mil-Std 1388-1B consisting of 05 task sections in iterative way as shown in the Fig. (2.6). ILS engineers are compelled to adapt these tasks to the requirements of any military system under study. As shown in the figure (2.4), ILS analysis is carried out iteratively throughout concept, feasibility, project definition and post production phases to influence system design. Over the years, other guidelines have been issued to improve the management of military procurement. The US logisticians have realized that Mil Std 1388 structure is too rigid and ILS benefits are difficult to measure.

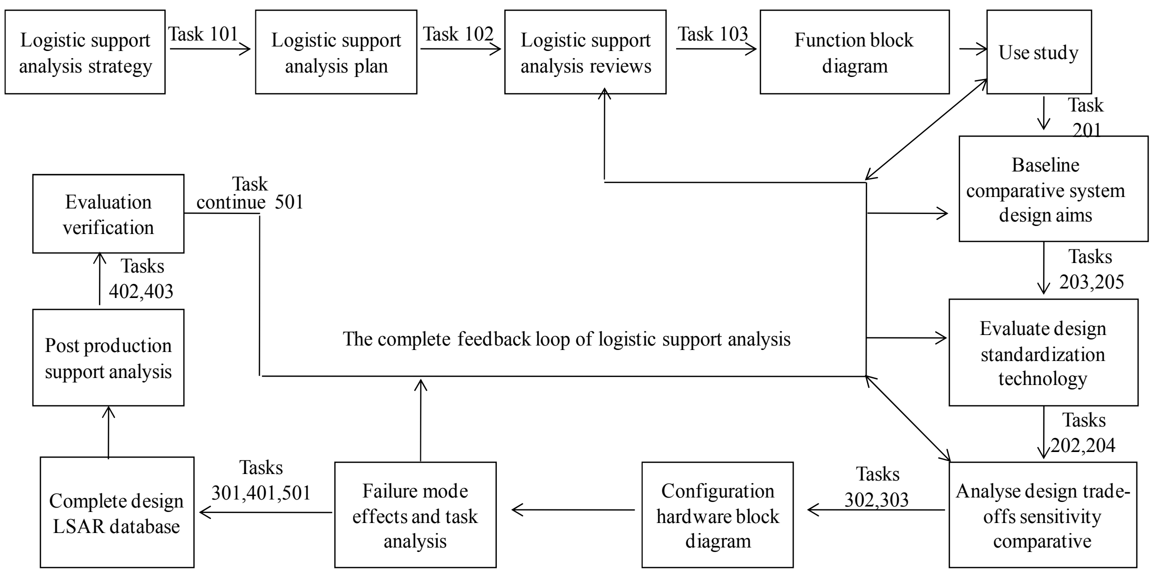

Fig. (2.4): Military ILS Process (US DOD, 1983)

Nowadays, the US standards have moved from the previous standards to a new defence Handbook 502, called Acquisition Logistics Handbook. The principal amendment is the shift from the mandatory status to the guidance presented by the Handbook. Alike the US

Mil-Std 1388, the UK Defence Standard is (Def Stan 00-60). The latter has received critics from industry practitioners for being too rigid, expensive and difficult to manage and as a result a new guideline is being issued under the name Product Life Cycle Support (PLCS) initiative.

2.6 LOGISTIC SUPPORT ANALYSIS (LSA)

LSA is the selective methodology used to achieve a reliable, maintainable and supportable system at the least whole cost of ownership by considering logistic support aspects. Scientific and engineering efforts that underpin LSA are reliability centred maintenance, operating and support cost estimation, trade–off analysis for repair versus discard decisions, and mathematical techniques for optimising repair levels and spare part provision. LSA is carried out by applying tools and techniques, typically:

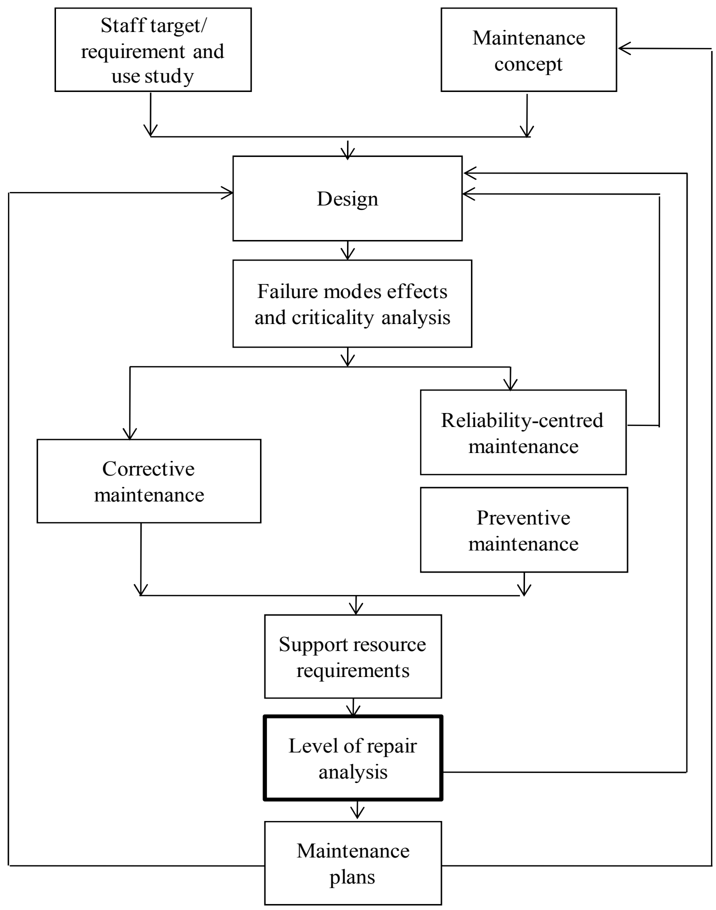

Fig. (2.5): System supportability Process (Blanchard, 1998)

- Failure Modes Effects Analysis and Criticality Analysis (FMECA);
- Reliability Centred Maintenance (RCM);
- Faulty Tree Analysis (FTA);
- Level of Repair Analysis (LORA);

Figure (2.5) shows the LSA diagram adopted by military asset managers (US DOD, 1983). As it is shown, they suggested that different LSA tasks should be integrated with maintenance process before the final maintenance plans are made. They also noted that the diagram provides a recycle process to refine the options under study or to generate new alternatives if the final decision is inconclusive. Besides, the included loops are the basic nature of design as an iterative methodology. LSA outputs are in a shared database, which include data related to FMECA, RCM, FTA and LORA, to be used by designer and logistics engineers.

From logistics support point of view, during all system phases, LSA is applied in parallel with system development. A prerequisite for an efficient support provision is an intensive cooperation between maintenance, logistics and configuration managements. For instance, in the project definition period, the system component and the maintenance strategies have to be identified. These maintenance strategies are generally based on repair site configuration and their spare part inventory. This task is called by level of repair analysis LORA and spare part inventory control. However, during the operation phase, these ILS elements (level of repair analysis LORA and spare part inventory control) may change when the conditions assumed at the design phase differ from those of operational use. Furthermore, support resource identification is also subject to maintenance strategies of the manufacturers or the users. Consequently, these changes may affect significantly ILS concepts and hence the LORA and spare part inventory control have to be reconsidered. Finally, at the end of the operation period, ILS concepts try to balance between maintaining a certain minimum level of functionality and minimising the spare part inventory to avoid its obsolescence when the system is dismantled.

ILS engineers consider LSA decision as a difficult task to developing an inclusive ILS strategy since it consists of the identification of various ILS elements, which are all strongly interrelated. The geographic repair distribution, the repair capacity and spare part control, among others, must be managed optimally to each other to provide cost-effective decisions. Often, it entails a complex trade-off analysis between designing reliable items, system reliability, availability, maintainability and supportability, operation requirements, and various cost elements. Level of repair analysis LORA and spare part inventory control optimisation not only improve system readiness but also save money. Plenty of spare part inventories require less maintenance and fewer repair capacity. The relationship between LORA and spare part inventory control is therefore critically important in ILS technique. Managers struggle to minimise logistics support (repair shops, maintenance manpower, and spare part inventories) and also to maximise the number of available systems. For instance, poor logistics support (e.g., lack of spare parts, personnel, and repair capacity) increases repair time which in turn decreases system readiness and availability. The joint LORA and spare part optimisation problem is to set the optimal compromise taking into consideration system performances, operation budget and requirement.

2.7 THE JOINT LORA AND SPARE PART OPTIMISATION PROBLEM

Spare part availability is an important issue for efficient system operation. When a failure occurs, the system downtime can be considerably reduced if sufficient spares are immediately available. However in an out-off-stock situation, lack of spares may cause costly production losses if repair time is long. It is evident that keeping plenty of spares in stock decreases system downtime at costly inventories and an ample repair capacity minimises also system downtime at costly repair investment. Consequently, it is important to achieve system operation performance by the contribution of these two ILS factors (Figure 2.6). A trade-off analysis of repair capacity and spare part inventory is therefore a cost effectiveness maintenance strategy.

The LORA (Level of Repair Analysis) is an ILS tool that facilitates the assessment of the repair tasks contributing to the whole life cycle cost. This assessment is intended to select: (1) the optimal repair-shop structure which is coherent with maintenance strategies; (2) the required support resources at each shop; and (3) the best repair decisions for any item that composes the entire system (US DOD, 1983; United Kingdom Ministry of Defence, 1996). These decisions refer to repair at the nearest shop, discard or repair at other repair shops. Practical methods of LORA evaluation are presented as an integer programming model that minimises support cost according to a desired level of system availability. A detailed description of this integer optimisation method applied to LORA analysis has been given by (Barros, 1998 and Baros, et al., 2001). In practical problems of LORA analysis, the great number of repair structure layers and the number of system items that need to be evaluated make it difficult to employ traditional optimisation techniques (Bricks, 2007). For instance the total number of possible solutions for a system which is made up of 22 items and repaired in a three echelon repair structure is 6.28×10^{10} (Saranga, et al., 2006).

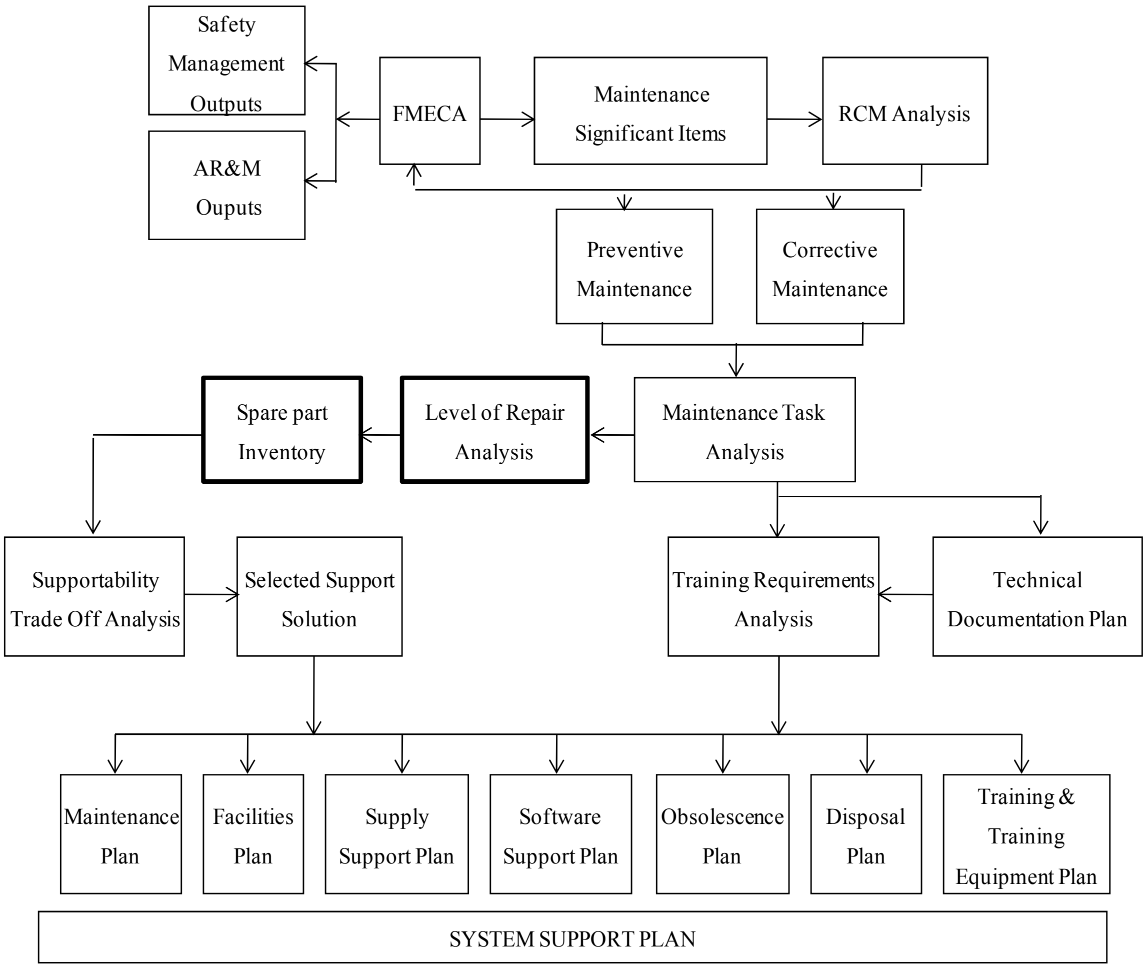

Fig. (2.6): System supportability Process, (US DOD, 1983)

On the other hand, spare part is an important factor contributing to maintenance costs. The latter often includes cost of repair tasks, cost of maintenance equipment and spares cost of system downtime when a failure occurs. Besides, the downtime costs are mainly considered as the spare shortage or the penalty cost. This shortage may lead in some situations to catastrophic results. (Sherbrooke, 1968; Wu, et al., 2008 and Markeset, et al., 2003) argued that maintenance delays in practice are the result of unavailable spare parts and other support resources when they are requested. To overcome this barrier, there is always an excess of spare stock even though at considerable inventory costs. The efficient spare part management according to ILS procedure is based on a trade-off between spare part stock and other maintenance factors related to system downtown reduction.

This trade-off can be optimised jointly rather than separately of support resources and spare part inventory. For instance, LORA and spare parts inventory are generally treated independently or sequentially. Studies on relevant fields in maintenance have mainly focused on inventory management; however, relatively little attempt has been dedicated to their joint optimisation, which is the basis of this study. To the best of our knowledge so far, this LORA and spares relationship has only been studied in recent work by (Basten et al., 2009). Another important interest is the choice of mathematical method that can handle the joint optimisation of these two ILS elements.

2.8 SUMMARY

The basis of the ILS technique and its implementation has been presented. The selection of support alternatives has proven to be complex to guarantee operational and maintenance provision for nowadays systems. The related literature has highlighted that the selection of any support resources is a combinatorial system and operation parameter optimisation. ILS has drawn quite a great attention these decades in different industries due to concerns about operation and maintenance costs.

Many ILS tools have been developed and several successful uses have been reported in aviation and military fields. Despite this, there are many challenges in getting widespread use of ILS tools. Part of the challenge is that these ILS elements are not optimised as a group as assumed in the ILS technique. As argued in section 2.7, there is very little work in that area. Furthermore, this chapter has shown that system operational availability is a function of level of repair analysis (LORA) and spare part provisioning during in service system lifespan. Their joint optimisation is attended to achieve the required level of system operational availability for the specified multi-echelon operation and support configuration. In the next chapters, the LORA will be set against the optimal spare part inventory to establish relationships between operation costs and system performances.

CHAPTER 3 LEVEL OF REPAIR ANALYSIS (LORA)

3.1 INTRODUCTION

The previous chapter has provided a critical review of literature dealing with the integrated logistics support technique. This review has investigated the issues of support resource optimisation and, particularly, the repair capacity and spare part optimisation. This chapter focuses on level of repair analysis LORA, an ILS element aiming at optimising the investment on repair facilities. It will briefly highlight raised issues regarding LORA economic evaluation models that should fit the characteristic of petroleum equipment maintenance.

The chapter is organised as follows. Section 3.2 presents a background to situate the importance of LORA within maintenance strategy development. The concept of LORA is introduced in Section 3.3. The interaction between maintenance and LORA is proposed in Section 3.4. The requirements of cost categorisation for LORA analysis is given in Section 3.5. This is followed by a discussion of the LORA optimisation problems and models in Section 3.6. Finally, the main findings of the chapter are summarised in Section 3.7.

3.2 BACKGROUND

The ever growing complexity of modern assets has led to an increase of cost-effective tools to meet operational requirements in an optimal and least cost way. Maintenance and its support activities, which should ensure a high level of systems and client satisfaction, play a key role in asset management. Repair of these systems have received considerable attention, due to the costly investment in maintenance and the required level of the system availability (Tysseland, 2007; Alfredsson, 1997; Brick, et al., 2009 and Blanchard, 1998). Focus has been put on the identification of the cost effective repair actions by trading-off the repair costs against the system downtime costs. Besides, modern repair structures are distinguished by their hierarchical complexity to perform their tasks. In addition, in some industries the same systems are installed in sparse areas to deliver their intended functions such as: aviation, military, petroleum and maritime. The operation performance depend, therefore, on how close is the support facilities to the operation sites. Consequently, some industries have become aware of the large potential for cost reductions by adopting whole life techniques in their acquisition process. Level of repair analysis LORA is one of the prescribed techniques in the military and maritime industries to achieve a system design with the minimum whole life maintenance cost (United Kingdom Ministry of Defence, 1996 and Defence Standard 00-60, 1983).

3.3 DEFINITION OF LEVEL OF REPAIR ANALYSIS (LORA)

Level of Repair Analysis, LORA, is a structured methodology to identify the cost of both repair alternatives and repair levels by considering cost of: spare parts inventory, manpower and support equipment (Blanchard, 1998). It evaluates the cost of any repair option based on maintenance action, requested ability of manpower, MTBF of system items, repair equipment needed, and economic criteria. The LORA approach was developed by military industry to plan maintenance tasks, to set up logistics resource allocations and to change the design accordingly. When a failure occurs, failed components are removed and repaired or replaced by new spare parts. When designing systems, level of repair analysts considers all aspects of the system design and maintenance scenarios to achieve required availability and cost balanced systems. As a result, they provide essential support requirements for the most effective maintenance strategy under predicted operational environment. The maximum benefit of LORA implementation is obtained by performing it at the early stages of system design and system operation.

The fundamentals of LORA process are given where after. First, for a given design in repair network, LORA analysts decide which components to repair or discard, where to perform such tasks, and finally where to install the required maintenance resources. Then, a number of reparation locations in which systems, subsystems and components have to be repaired or discarded is set up to satisfy maintenance requirements at minimum cost. The LORA is an iterative analysis that should interact with the design process. Table 3.1 summarises the LORA contribution all over the system life cycle.

Table (3.1): LORA and the Product Life Cycle (Pecht, 2009)

System Life-Cycle Phase	Function of the LORA	LORA Data and Source
Program initiation and concept exploration	Conduct trade-off studies of: Maintenance concept: evaluate possible support scenarios System support: new or existing Conduct operational effectiveness analysis to Develop WLC estimate for budgetary planning Identify noneconomic constraints to supportability and level of repair	R&M and WLC data from existing fielded systems Predictions
Design and development	Influence design for maintainability and testability Identify preliminary quantitative requirements for system support, facilities, personnel, and provisioning of major assemblies Make repair and discard decisions Evaluate WLC impact of proposed design changes	R&M predictions LSA Developer budgetary cost estimate
Production and initial fielding operations	Make level of repair decisions Determine provisioning requirements to include user/on-site spares and maintenance-site repair-part inventory Evaluate WLC impact of proposed design changes Review and assess effectiveness of logistics system support Update provisioning lists Assess the WLC impact of proposed design changes	LSA Test results R&M prediction design-change proposals design changes Field maintenance and cost data

LORA: level of repair analysis
LSA: logistics support analysis
WLC: whole life costing
R&M: reliability and maintainability

In the literature, various models of LORA have been discussed for a three echelon repair network (Figure 3.1) and multi-indenture system (Figure 3.2). Carrying out LORA studies is quite complex, given the number of components in the installed systems (Barros, 2001; Basten, 2009; Gutin, 2005 and Saranga & al., 2006). Therefore, LORA models which involve a large number of decision variables are very difficult to optimise by means of traditional optimisation techniques. For instance, the number of all possible combinations (part, repair and discard decision) for a system consisting of 32 parts spread between different indentures is 6.28×10^{10} (Saranga & al., 2006). Hence, techniques like integer programming and branch and bound method become difficult to use.

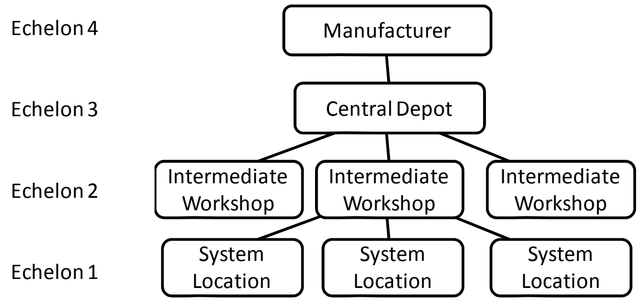

Fig. (3.1): A multi-echelon repair network (Basten, 2009)

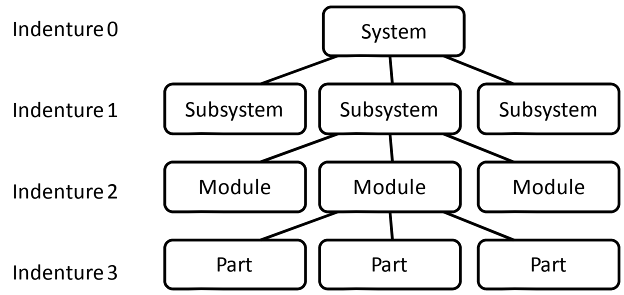

Fig. (3.2): A multi-indenture system (Basten, 2009)

Pecht (2009) stressed on the following issues that have a great impact on LORA decisions (repair and discard decisions):

- Assessment of changes in repair decisions due to variation of uncertain input parameters should be done through sensitivity analysis. These parameters may include: mean time between failure MTBF, mean time between maintenance MTBM, mean time to repair MTTR, etc. Even though sensitivity analysis is univariate approach, its main advantage relies on the identification of parameters that have a great influence on repair decision changes.

- When condemnation takes place (i.e. not every failed component can be repaired), it is imperative to consider repair yield and condemnation rates. Pecht (2009) noticed that the decision to repair may vary at low repair yield or high condemnation rate.

- The cost related to some shared logistics resources (e.g., resources that serve a number of components) must be amortized over all the components. If the LORA decision results of that a component no longer needs the resource, another LORA analysis should be carried out to reproduce the change.
- When new and costly support equipment is required, acquisition decision may involve performing LORA analysis along with whole life costing approach.

3.4 MAINTENANCE & LORA

Maintenance strategy is defined as a framework outlining procedure on when, how and where maintenance tasks take place (Blanchard, et al., 1991). A brief overview of the framework with respect to its application to repair practice was presented by ISO/IEC (2004). The framework depicts the relation between the repair echelons, the system indentures and the levels of repair which is considered as the most relevant to any system components. Hence, this framework is viewed as a general methodology of the maintenance and its support resource provision based on the policies of manufacturers and system users (ISO/IEC, 2004).

A repair echelon is a location where a predefined group of maintenance tasks are carried out on specific components. Blanchard (1998) claimed that the structure of the configuration of the repair locations is subject to the system-of-interest, its mission characteristics, its operation zone, the interrelationship with other repair echelon, and cost effectiveness of maintenance activities. However, the indenture levels are the system decomposition from the maintenance action point of view. For instance, indenture levels are: system, subsystem, equipment and component (Blanchard, 1998).

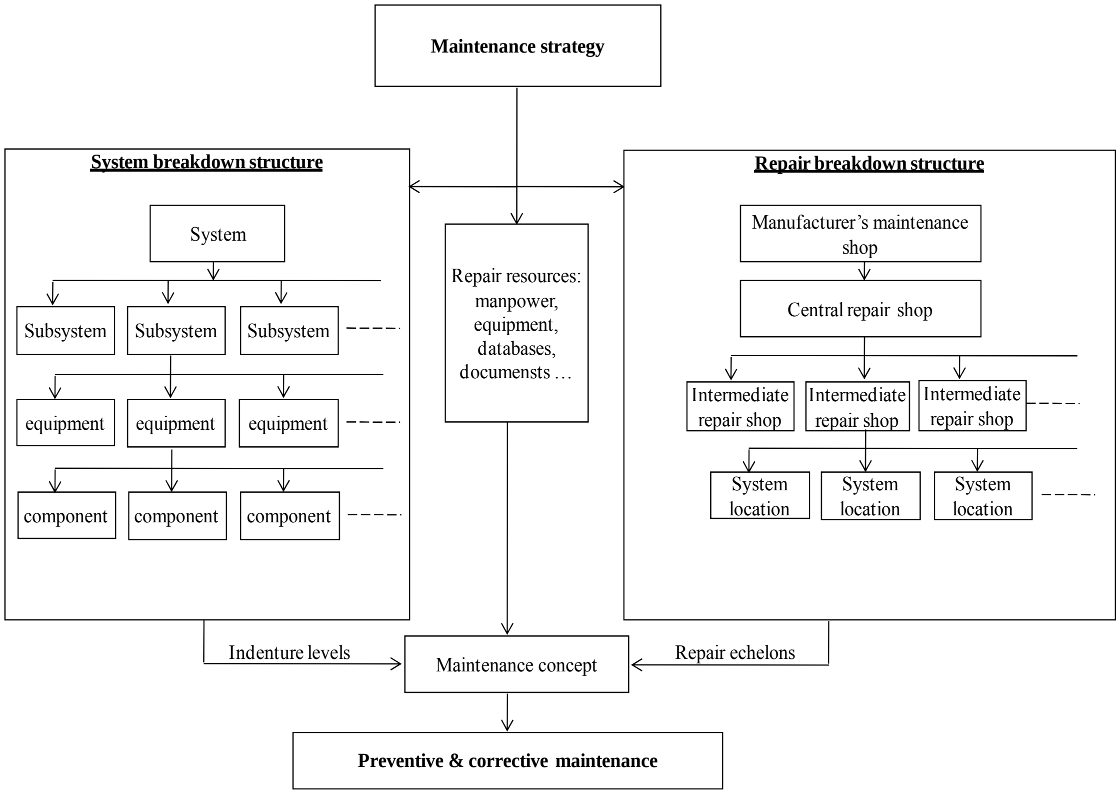

Fig. (3.3): Preventive and corrective maintenance strategy (ISO/IEC, 2004)

Figure 3.3 describes the optimal development of maintenance concepts for preventive and corrective tasks by considering both repair structure and system breakdown structure. Spare parts are in general provided through a multi-echelon structure, which is a top-down structure consisting of many layers of repair shops as shown in Figures 3.1 & 3.2 (Rustenburg, et al., 2001; de Smidt-Destombes, et al., 2005 and Sleptchenko, et al., 2002). The main objectives of these facilities are twofold: (1) stoking and supplying spare parts and (2) repairing failed components. Shops at the down layers directly provide spares to installed systems, while those at a top layer provide spares to its subsequent layers. Besides, repair shops at a top layer are typically equipped with the most sophisticated repairing capacities. That is, a part that cannot be repaired by a particular facility would be sent upward to the central maintenance facility.

The dynamic and reactivity of repair tasks linked to maintenance of complex systems stresses on the importance of appropriate LORA to maintenance policies (Barros, 2001; Basten, 2009 and Gutin, 2005). As stated above, the main objective of LORA is to ensure a prompt spare and repair provision to failed systems by optimising both system performances and maintenance costs, i.e. making the right spare and repair available at the right time and at the right place (United Kingdom Ministry of Defence, 1996). Analysing level of repair is: (1) a maintenance content management, which addresses "what and why to provide"; (2) a maintenance period management, which deals with "when to provide"; (3) a maintenance approach management, which refers to "how to provide" and (4) a maintenance location management, which addresses "where to deliver". In addition, maintenance engineers classify all elements of the system structure into two categories: replaceable and discard items (Wu et al., 2008). The replaceable units or components stand for items that can be repaired; which in turn entail two types of units: line replacement units (LRU) and shop replacement unit (SRU). An LRU is a failed item that can be removed from the installed system individually, replaced by a new item, and shipped out to repair echelons for repairing. Inversely, an SRU is a failed item that cannot be removed from the installed system individually alike an LRU. In this case, its LRU parent is removed from the system, replaced by a new LRU and sent to repair shops where it can be disbanded, and the failed SRU can be removed for repairing, and replaced by a new one (Jones, 2006 and Blanchard, 1991).

Table (3.2): Repair configuration in a Multi-Echelon Logistics Support (Petch, 2009)

System location or Organisational Level	Failures originate at the organisational level and are isolated to a line replaceable unit (LRU). The faulty item is removed from the system and replaced with a spare one. The system is checked for proper operation. The faulty item is sent to the nearest repair shop.
Intermediate Level	The LRU is repaired by isolating the faulty shop replaceable unit (SRU). The faulty SRU is removed and replaced with a spare one. The repaired LRU is checked for proper operation. Once the LRU is repaired, it is sent to the organisational level or to an inventory control or storage point. If no fault is found, the LRU is also sent to the inventory control or storage point. Occasionally, the LRU cannot be repaired by the intermediate level and it is sent to the depot for repair.
Depot	The SRUs (and sometimes LRUs) are repaired. The faulty component is removed and replaced. The SRU (or LRU) is checked for proper operation. Once the repair is complete, the repair unit is sent back to the intermediate or depot level inventory control or storage point.

A discard units or components stand for items that are non-repairable, which also entail two types: a discard unit DU and a discard part DP. In a similar way, DU is an item that can be removed individually from the installed systems, whereas DP cannot but its parent LRU can be removed individually. A failed DU is directly removed from the system, replaced, and then discarded. However a failed DP involves taking its LRU out of the system and sending it out to repair shop where the defeated DP is removed and discarded (Rustenburg, et al., 2001; de Smidt-Destombes, et al., 2005 and Sleptchenko, et al., 2002). The table 3.2 enumerates the mean repair tasks through the repair network.

In summary, the preventive and corrective maintenance strategy is intended to reduce the time of system malfunctioning by identifying the most effective decisions, which are related to repair, replacement and discard tasks. Since repair facilities and spare parts are quite expensive for complex systems, much of maintenance effectiveness requirement is the trade-off between the stocking policies and repair investment (Kleynera, et al., 2008). Consequently, the LORA plays an important role in addressing these maintenance questions. Its main objective is to emphasize on the optimal provision of spare and repair services with respect to maintenance needs. Another objective is to emphasize the need to include the aspects of the whole supply chain in the analysis and to increase the collaboration between the parties at planning stages.

3.5 LEVEL OF REPAIR COST ANALYSIS

The whole life costing WLC is a widely used method to estimate costs in the economic assessment of any investment option (Lindholm, et al., 2005) and will be used to generate all costs in LORA model. A need of adequate WLC formula for LORA analysis lies firstly in the development of cost categorisation based on the type of system and various maintenance tasks. Secondly, on how easily it can be implemented for an efficient supportability tool. A detailed definition of WLC can be found in (Kishk et al., 2001), they consider WLC as a systematic technique that includes of all costs and revenues associated with the acquisition, use and maintenance, and disposal of an asset. It evaluates the whole life cost of an option under study, where the net present value, of all costs and the salvage value of that option is:

$$NPV = IC + \sum_{m=1}^{nno} PWO_m F_m + PWA \sum_{j=1}^{nar} A_j + \sum_{k=1}^{nnr} PWN_k C_k - PWS \cdot SAV \qquad (3.1)$$

Where

$$PWO_m = (1+r)^{-t_{im}} \tag{3.2}$$

$$PWA = \frac{1}{r}\left(1-(1+r)^{-T}\right) \tag{3.3}$$

$$PWS = (1+r)^{-T} \tag{3.4}$$

$$PWN_k = \frac{1-(1+r)^{-n_{ik} f_{ik}}}{(1+r)^{f_{ik}} - 1} \tag{3.5}$$

$$n_{ik} = \begin{cases} \text{int}(\frac{T}{f_k}), & \text{provided that rem}\left(\frac{T}{f_k}\right) \neq 0 \\ \frac{T}{f_k} - 1, & \text{elsewhere} \end{cases} \tag{3.6}$$

Where:

C_0 is the initial cost, SAV is the salvage value, and $nno, nar, \text{and} nnr$ are the number of one-off future costs, F_m, annual recurring costs, A_j, and non-annual recurring costs C_k, at frequencies f_k, respectively.

PWO_m: Present Worth of One-Off future costs

PWA: Present Worth of annual recurring costs

PWS: Present Worth of Salvage Cost

PWN_k: Present Worth of non-annual recurring Cost

Generally, a LORA is primarily employed at early system phase as maintenance cost analysis to influence the design changes with regard to cost and repair parameters. The inclusion of WLC in conjunction with the LORA procedure provides the ability to identify the repair aspects that contribute to total cost reduction. However, WLC equation (3.1) should be reorganised according to LORA requirements and particularly according to a generic cost breakdown structure CBS that combines both LORA activities and their related costs. The CBS of LORA includes:

- Repair Facility Cost
- Manpower Cost
- Test and Maintenance Equipment Cost
- Spare Part Cost

- Spare holding Cost
- Technical Documentation Cost
- Transportation Cost

As such, WLC under LORA analysis deals with two types of cost categories: one for fixed repair cost element, and the other for variable maintenance cost. Consequently, the WLC formula should be different from the equation (3.1) for the LORA purpose. The reasons are given as follows:

- In LORA optimisation, the objective function and constraints are generally related to item failure rates.

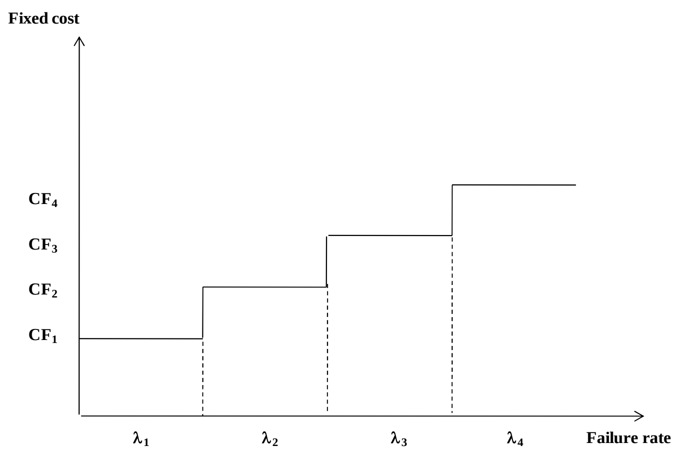

Fig. (3.4): fixed repair cost evolution

- Fixed repair costs are generally the common costs that do not vary with the failure rate changes. Since the installed capacity can only bear a certain level of repair demand, i.e. failure rates, these costs are fixed only within a defined failure rate interval. Therefore, this cost category should be modelled by steps as shown in the figure (3.4). Besides, these costs are also defined for a given repair echelon and system indenture.

- Variable repair costs are modelled as a continuous function which varies with the failure rate changes; e.g.: spares costs. This cost category is calculated for all LRU and SRU, and all repair echelons.

In the case of LORA studies, the optimisation variables represent the repair decisions including repair, discard and move to another repair echelon for any system LRU, and SRU. As a result, logistics engineers are compelled to identify both fixed and variable costs related to the above three decisions. According to equation (3.1), LORA modelling costs should be restructured into fixed and variable cost for any item as follow (Barros, 1998):

$$NPV_{repair} = FC_{repair} + \sum_{k=1}^{N} \frac{\lambda_{repair} * VC_{repair}}{(1+r)^k} \tag{3.7}$$

$$NPV_{discard} = FC_{discard} + \sum_{k=1}^{N} \frac{\lambda_{discard} * VC_{discard}}{(1+r)^k} \tag{3.8}$$

$$NPV_{move} = FC_{move} + \sum_{k=1}^{N} \frac{\lambda_{move} * VC_{move}}{(1+r)^k} \tag{3.9}$$

Where: λ_{repair}, $\lambda_{discard}$ and λ_{move} denote the annual demand for repair, discard, and move respectively. According to Barros (2001), the following three LORA-based variables can be used to compare repair alternatives.

$$\begin{cases} X_{\mathrm{r,e},i} = \begin{cases} 1 & \text{if repair option r at echelon e is selected for part i} \\ 0, & \text{otherwise} \end{cases} \\ X_{\mathrm{d,e},i} = \begin{cases} 1 & \text{if discard option d at echelon e is selected for part i} \\ 0, & \text{otherwise} \end{cases} \\ X_{\mathrm{move,e},i} = \begin{cases} 1 & \text{if move option m at echelon e is selected for part i} \\ 0, & \text{otherwise} \end{cases} \end{cases} \tag{3.10}$$

Finally, the whole life cost of any repair alternative could be written as follow:

$$NPV = \begin{cases} \sum_{i}^{iitem} \sum_{e}^{echelon} (FC_{repair} + \sum_{k=1}^{N} \frac{\lambda_i * VC_{repair}}{(1+r)^k}) * X_{r,e,i} + \\ \sum_{i}^{Item} \sum_{e}^{echelon} (FC_{discard} + \sum_{k=1}^{N} \frac{\lambda_i * VC_{discard}}{(1+r)^k}) * X_{d,e,i} + \\ \sum_{i}^{Item} \sum_{e}^{echelon} (FC_{move} + \sum_{k=1}^{N} \frac{\lambda_i * VC_{move}}{(1+r)^k}) * X_{d,e,i} \end{cases} \tag{3.11}$$

Therefore, the LORA optimisation function can be formulated in this way depending mainly on the number of echelon and the number of items according to system and repair structures.

3.6 LORA OPTIMISATION PROBLEMS

The most economical maintenance strategy for any component of system is to decide whether it is worth repairing or discarding it. Level of Repair Analysis (LORA) is an approach which examines the cost balance between repairing the component and discarding it. The framework of this approach is an iterative process ensuring the optimum maintenance planning. However, the LORA problem as combinatorial optimisation is not the most widely studied in the literature (Basten & al., 2006). Limited works were devoted to solve the LORA problem. Barros et al., (2001); Saranga et al., (2006); Gutin et al., (2005) and Basten et al., (2009) modelled LORA as an Integer Programming model in which all repair locations at the same echelon were aggregated. Besides, they all resolved their model under infinite capacity of resources. Brick et al. (2009) model LORA without aggregating data per echelon level for only 1 echelon and 2 indenture levels.

Barros & al. (2001) presented a mathematical framework as an Integer Programming (IP) model resolved by branch and bound algorithms. In this model the objective function has two elements: a fixed cost FC of setting up maintenance facilities (test equipment, labour manpower, and technical data); and a variable cost VC of ordering and holding spare parts. The goal of this IP problem is to find a subset of repair decisions that minimises the total maintenance costs while satisfying parts relationship and maintenance resource constraints. They have assumed that any installed maintenance capacity (fixed cost) performs reparation to all components belonging to the same indenture. Brik et al. (2009) work treated the applicability of location of facilities and the installation of capacitated resources to LORA problems. They have proposed a mixed-integer problem MIP model for the discrete location of facilities and installation. Gutin et al. (2005) formulated the LORA problem as an optimisation homomorphism problem on bipartite graphs and they proved that the LORA problem is an NP-hard problem. Saranga et al. (2006) adopted the same Barros Integer Programming model but with different fixed cost allocation. They considered that any component bears a specific fixed cost whereas in Barros model all components at the same indenture share the same fixed costs. Furthermore, Sarraga et al. have solved LORA problem by using the genetic algorithm software evolver. Basten et al., (2009) proposed an Integer Programming model that generalises the existing models (Barros model and Saranga model) by allowing a predefined set of components to share the same fixed costs. In addition, they modelled the LORA problem as a minimum cost flow problem with side constraints.

In real-world problems of LORA analysis, a number of repair shops with a vast number of system items that need to be assessed make the optimisation of LORA model difficult to use traditional techniques. As discussed above, the given LORA optimisation problem is known to be in the class of NP-hard problems. Consequently, all the traditional solution methods may attain the optimal solution. However, their computational time to achieve the solution may increase exponentially as the number of variables increases. Therefore, to solve this kind of optimisation problems an efficient tool that involves minimal requirements to solution space should be chosen. A genetic algorithm (GA) and TABU-SEARCH offer all these features and can be used for optimisation when solution space is of a set of binary values or for combinatorial optimisation. Besides, this technique has been proven to be an efficient optimisation tool in reliability engineering. The main areas of GA application in reliability engineering and maintenance are system design optimisation, fault diagnosis, and maintenance optimisation (Zdanski, 2002; Coit, et al., 1996; Gen, et al., 2000; Dengiz, et al., 1997 and Zhou, et al., 2000).

3.6.1 NOTATION

The following notations are adopted herein:

m the number of the echelons in the repair network.

n the total number of components for the system under consideration.

Component i is the parent of the component j or component j is the child of the component i

r repair options: repair, discard or move.

λ_i total number of maintenance tasks required in the whole life time of component i.

$FC_{r,e,i}$ fixed cost related to repair option 'r ' at echelon e, for component i.

$VC_{r,e,i}$ variable cost related to repair option 'r' at echelon e, for component i.

X vector containing three binary values (3.12) which should have be defined for any item and at any echelon.

$$\begin{array}{cccc} & repair & discard & move \\ X = & [1 or 0 & 1 or 0 & 1 or 0] \end{array} \tag{3.12}$$

3.6.2 MATHEMATICAL EXPRESSIONS

The binary LORA problem is formulated based of the notation mentioned above as follows:

$$X_{r,e,i} = \begin{cases} 1 & \text{if repair option } r \text{ at echelon } e \text{ is selected for part } i \\ 0, & \text{otherwise} \end{cases} \tag{3.13}$$

$$\sum_{i=1}^{N} \sum_{r=1}^{3} \sum_{e=1}^{m} \left[VC_{r,e,i} \; \lambda_{it} + FC_{r,e,i} \right] X_{r,e,i} \tag{3.14}$$

Subject to

$$X_{\mathrm{r},\, 1,\, i} = 1 \qquad \text{for all parts} \tag{3.15}$$

$$X_{\mathrm{move},\ \mathrm{e},\, i} = \sum_{r=1}^{3} X_{\mathrm{r},\ \mathrm{e}+1,\, i} = 1 \tag{3.16}$$

$$X_{\mathrm{r},\ \mathrm{e},\ j} = X_{\mathrm{r},\ \mathrm{e},\ i}$$
$$\forall \text{ e and (i is parent of j) where r = discard or move} \tag{3.17}$$

The objective function given in equation (3.14) sums the fixed and variable costs of performing repair, discard and move actions. The constraint given in equation (3.15) ensures that one repair option is chosen at echelon one. If a move decision is taken at echelon e, only one repair decision should be taken at echelon e+1 (constraint given in equation (3.16). Otherwise, no repair option is chosen at echelon (e+1).

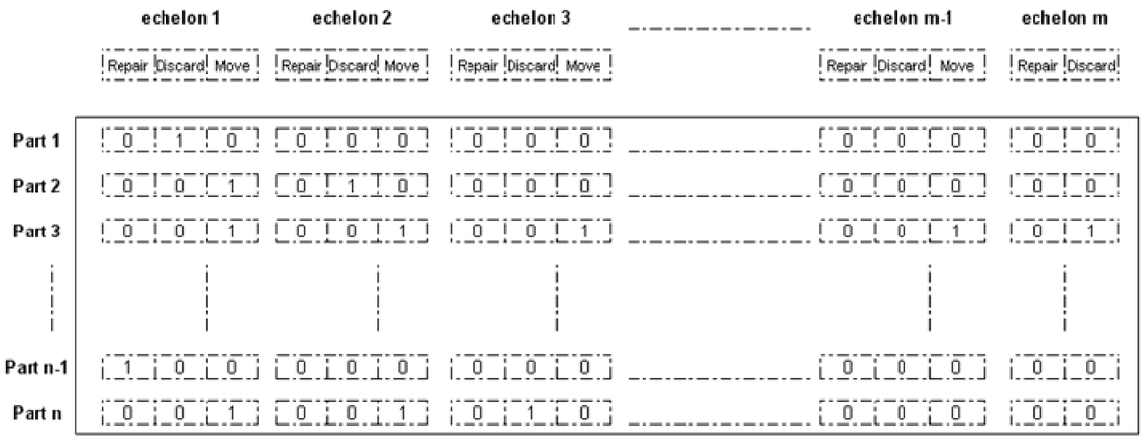

Fig. (3.5): LORA space solution

The equality constraint given in equation (3.17) requires that all the enclosed lower indentures of any subsystem have the same decisions of the subsystem itself with respect to the replacement and move options at different echelons. The last constraint requires that there are only two repair decisions (repair or discard) at the highest echelon. Figure (3.5) represents a sample of possible solution generated randomly by taking into consideration all the above constraints.

3.7 SUMMARY

The model of LORA presented in this chapter can be applied to evaluate the efficiency of repair decisions from a whole life cost point of view with a focus on the system breakdown structure and the repair network. In addition, this model gives a foundation on which to optimise. The total maintenance cost during all system life phases is optimised, and therefore the whole operation cost of the system is reduced. Including support parameters into the model with appropriate cost categorisation can potentially help to improve the system acquisition along with its repair facility installation by minimising the whole life cost of the system.

In addition, the proposed model that underpins LORA decision is a combinatorial binary optimisation problem known as an NP-hard problem. In particular, this chapter emphasises on meta-heuristic approaches, including the genetic algorithms and the tabu search method that have become more popular for combinatorial optimisation.

CHAPTER 4 SPARE PART INVENTORY MANAGEMENT

4.1 INTRODUCTION

The two previous chapters reviewed integrated logistics support ILS and its repair analysis element, namely, LORA. This chapter extends the discussion of ILS into another ILS element related to the management of spare part provision. In practice, the majority of organisations adopt a multi-echelon repair network to provide repair services and spare parts to their installed systems. The reason of this structure of repair and spare part supply is the scattering of systems over a huge geographical area. Therefore, this chapter focuses on identifying optimal spare allocation in the repair network by considering the effect of repair capacity.

This chapter presents a review on the existing literature about spare part inventory models and repair capacity models. A distinction is made between models focusing on optimal inventory allocation for a given repair structure, and models focusing on joint optimisation of repair structure and stock allocation. The first class of models tries to maximise system performances while minimising support costs through a predefined repair network. However, the second class of models tries to optimise the same objective functions in which the repair structure is considered as a decision variable. The study presented in this thesis focuses on the second class and therefore it is mainly related to finite repair capacity models.

This chapter begins by a background section (4.2) then by enumerating data requirement for spare part management in section (4.3). This is followed by a description of the METRIC model, which is broadly considered to optimise spare inventory in section (4.3). The mathematical framework to optimise spare inventory for multi-echelon and multi-indenture configuration is presented in this section. In section (4.5) a discussion of some specific limitations of the METRIC model and the solutions proposed in the literature is given. Section 4.6 introduces models based on queueing theory when service capacity is limited, such as M/M/K and M/G/K models. The elements described here constitute an approximation of repair and waiting times which should be combined with inventory model to reflect what is encountered in real-world situations. The computational algorithm for computer application is presented in section 4.7. The chapter concludes with the position the research presented in here in relation to the thesis framework.

4.2 BACKGROUND

Today's asset management developments reveal a recent intensive partnership between the different business actors. Corporation relationships between manufacturers and clients have become more common; there are industry guidelines for more integrated management approaches such as: integrated logistics support for the military industry (United States Department of Defence, 1983), Private Finance Initiative PFI for construction industry (Kishk et al., 2003), among others. Accordingly, more organisations are adopting a holistic based decision-making that relates design, manufacturing and operation phases. Within this new environment, clients are requiring more reliable products along with an efficient maintenance support. (Blanchard, et al., 1998; Diaz, et al., 1997 and Rappold, et al., B. D, 2009) assert that maintenance and its support represent the major contributor to whole life cost for many types of systems. To this end the integrated logistic support ILS, which is a methodology to identifying and optimising maintenance resources in order to preserve a desired level of system performances, plays important role in achieving these requirements.

Another actual tendency is characterised by the fact that current technological equipment such aircraft, petroleum, medical and military equipment are becoming more complex and scattered over a huge geographical area (Sleptchenko, et al., 2005; Rustenburg, et al., 2001; de Smidt-Destombes, et al., 2007 and Cohen, et al., 1999). Besides, they have complex structures that malfunction because the enclosing items are either failed or worn out during operation. One way to ensure a high level of system availability is to hold enough spare parts to provide an immediate replacement of the failed items. Nevertheless, holding enough spares may be very costly and risks being obsolete over time; thus a balance between cost of spares and system availability is necessary. These issues are already challenging for systems consisting of thousands of items structured in several levels called the multi-indenture systems. In addition, these systems may be installed at different locations, in which case maintenance facilities should be needed at the local levels, intermediate levels and the central level: this is called the multi-echelon repair network (Lau, et al., 2006 and Kim, et al., 2007). The spare part allocation is, therefore, an optimal supply throughout all pyramidal subordination of maintenance levels. This optimisation has been regarded as an important area for maintenance cost reduction and has been considered in the last decades by many researchers (Caggiano, et al., 2006; Lau, et al., 2006; Gupta, et al., 1992 and Kim, et al., 2000).

For literature on spare part optimisation, the evolution of the related models can be found in Sherbrooke, (1668); Muckstadt (2005); Kennedey, et al., (2002); Avsar, et al. (2000) and Sleptchenko, et al., (2002). In these papers, the area of study is devoted to multi-echelon inventory systems in which spare part is stored at different levels. In addition, this bulk of research in multi-echelon spare part inventory management can be categorised into two main classes: spare part optimisation under infinite repair capacity and under limited repair capacity. However, these two classes are based on METRIC model developed by Sherbrooke, (1668). In his model, also called METRIC or Multi Echelon Technique Repairable Item Control, all repair levels are supplied by intermediate levels or a central depot which in turn is supplied by the spare part manufacturers. When an item fails, it is sent out to repair and a spare is plugged in. If the spare part is not available, it is backordered from the preceding repair levels. As a result, all repair levels operate according to a continuous stocking policy (S - 1, S) and the considered model intends to maximise system availability subject to a budget constraint using marginal analysis (Sherbrooke, 1668). Besides, METRIC considers that the installed repair capacity is unlimited; therefore the repair time (or the number of components in repair) is assumed to independent. Other feature of METRIC model is first-come-first-served replenishment policy at all repair level and item failure rate is assumed to follow Poisson distribution. Consequently, the number of items at bases, in transportation or in repair is approximated to be Poisson distribution. Under the Poisson distribution, the mean of backordered items are equal to their variance.

4.3 DATA REQUIREMENTS

Data requirements for spare part management may be generally regrouped into three classes: technical-related data, support-related data and cost-related data. The first class encompasses: criticality, redundancy and commonality (Sec. 4.3.1). The second class encompasses all information related to support activities such as: repair location, storage location, repair time, transportation time, etc. The third class includes various costs associated with acquiring and stocking spare parts, and repair and maintenance tasks (Sec. 2.5.4).

4.3.1 TECHNICAL INFORMATION

Technical information is often provided by the Original Equipment Manufacturer OEM. The key objective of this type of data is to decrease the stock value and to manage inventory risk. However, asset managers do not usually focus on data collection for all parts. Parts that are relatively inexpensive and well supplied by different manufacturers, spending time on gathering technical data is not advantageous from a cost point of view. On the other hand, parts that are relatively costly or supplied by a small number of manufacturers, technical data collection is compulsory to control inventory risks and maintenance costs (Sherbrooke, 1992). The taxonomy proposed in the literature to the definition of spare part technical data is:

4.3.1.1 PARTS CRITICALITY

The criticality analysis is concerned with the impact of component failure on system functionality. Within this analysis, parts are classified into three main categories. Firstly, components that cause full system breakdown, i.e. the system is unable to deliver its assigned functions, are called critical or vital parts. Secondly, components that cause only a partial system breakdown, i.e. the system is operational for just a piece of its assigned functions, are denoted partially critical or moderate parts. Finally, components that have no effect on system functionality, i.e. the system can deliver its assigned functions but may result in more severe functional problems in the long run, are denoted non-critical or desirable spares (Prakash Gajpal, 1994).

The Norwegian standard for oil & gas industry (Z-008, 2001) categorises the failure impact on three types of consequences, as shown by the table (4-1).

Table (4.1): General consequence classification of part failure on system functionality (NORSOK STANDARD Z-008, 2001)

Class	Health, safety and environment (HSE)	Production	Cost
High	Potential for serious personnel injuries. Render safety critical systems inoperable. Potential for fire in classified areas. Potential for large pollution.	Stop in production. Significant, reduced rate of production, exceeding X hours (specify duration) within a defined period of time.	Substantial cost (specify cost limit)
Med.	Potential for injuries requiring medical treatment. Limited effect on safety systems. No potential for fire in classified areas. Potential for moderate pollution.	Brief stop in production. Reduced rate of production lasting less than X hours (specify duration) within a defined period of time.	Moderate cost between two limits (specify cost limits)
Low	No potential for injuries. No potential for fire or effect on safety systems. No potential for pollution (specify limit).	No effect on production within a defined period of time.	Insignificant cost less than a defined limit (specify cost limit)

Cohen et al., (1997) revealed that criteria used in analysis the part criticality are quite considerable in practice; however all of them are associated with the failure consequences and shortage penalties. Practically, criteria such as cost of spare part, system availability, HSE considerations and storage penalties are the most considered while analysing spare parts (Prakash Gajpal, 1994 and Sharaf, 2001). Figure 4.1 represents the hierarchy breakdown structure to measure part priorities based on VED (Vital, Essential and Desirable) analysis using Saaty's process (Saaty, 1990). For instance, the main objective of this process is to assess the part criticality, which appears at the top level of the hierarchy. The criteria used for assessment of the criticality figure at the middle level. In figure 4.1 the criteria that influence assessment of the criticality are : System availability, supply time, stock out implication, cost and type of spares. Alternative modes characterising each criterion are situated at the bottom level of the hierarchy. These modes may be: high, moderate, low and rare.

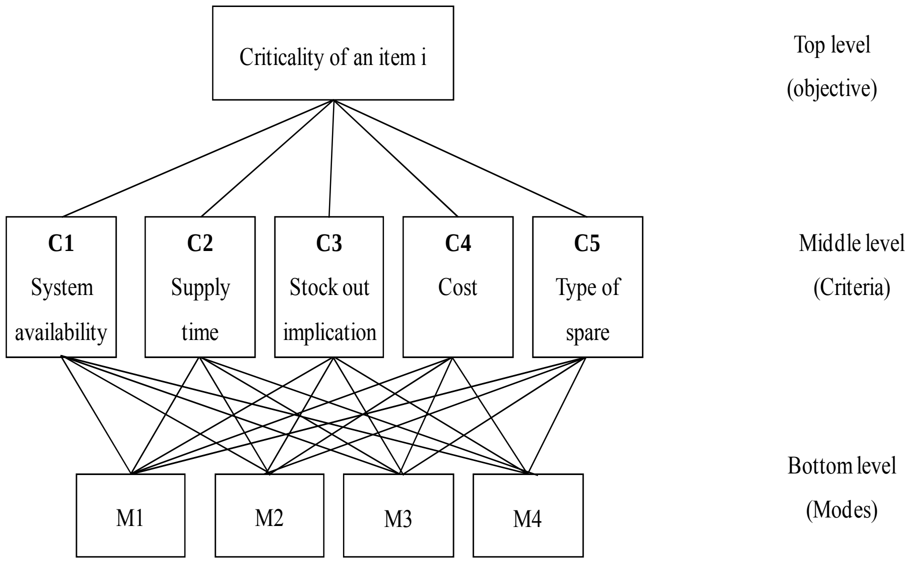

Fig. (4.1): The hierarchy breakdown structure for criticality analysis (Saaty, 1990)

The hierarchy structure using Saaty's process consists of three mean steps. First, criteria are identified and the weights that measure their relative values comparison are established (table 4.2). In doing so, pair-wise comparisons each pair of criteria is specified, and result of this comparison is a (n x n) matrix, where n represents the number of criteria considered. The normalised eigenvector associated with this matrix produces the weight of each criterion with respect to the main decision. Secondly, for each criterion, pair-wise comparisons each pair of modes are considered. Similarly, the result of this comparison can be presented by (m x m) matrix, where m stands for the number of modes. The normalized eigenvector of each matrix produces the weight of each mode with respect to the considered criterion. Thirdly, the final weights called the composite weights are determined such that the mode weights are multiplied by the criterion weight. The total score of the criticality analysis is the sum of its individual mode scores.

Once parts are classified according to their criticality, their repair jobs are labelled and served in accordance with a preference method: high-priority, moderate-priority and low-priority jobs. In this specification, high-priority jobs pre-empt medium-priority jobs, which in turn pre-empt low-priority jobs in the queue. Although Staay's process introduces some objectivity into the spare part analysis, it still has two limitations.

Table (4.2): The fundamental scale (Staay, 1990)

Intensity of importance on an absolute scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective.
3	Moderate importance of one over another	Experience and judgment strongly favour one activity over another.
5	Essential or strong importance	Experience and judgement strongly favour one activity over another.
7	Very strong importance	An activity is strongly favoured and its dominance demonstrated in practice.
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation.
2 -4 -6 -8	Intermediate values be-tween the two adjacent judgments	When compromise is needed.
Reciprocals	If activity *i* has one of the above numbers assigned to it when compared with activity *j*. then *j* has the reciprocal value when compared with *i*.	
Rational	Ratios arising from the scale	If consistency were to be forced by obtaining *n* numerical values to span matrix.

First, decision-makers are forced to attribute subjectively comparison scores according to their practical experience. This issue becomes more difficult for new introduced systems for which asset managers do not have a broad knowledge about the constituting components. Secondly, running the process for a system including thousands of items is difficult and time consuming.

4.3.1.2 PARTS REDUNDANCY

Redundancy can be employed with the intention to increase the system reliability without any change in the reliability of the individual parts that constitute the system. The major limitation of this approach is the increase in system cost and size. In practice, achieving high availability is commonly trade-off studies between designing systems with redundancy and keeping an ample spare stock for immediate replacements (Öner, 2011). Under redundancy, system functionality can be guaranteed by the two following levels. Firstly, within a subsystem i, redundancy entails that not all enclosure items should operate for the subsystem to function appropriately. Therefore, only a part of items should be operating that for subsystem i to function appropriately.

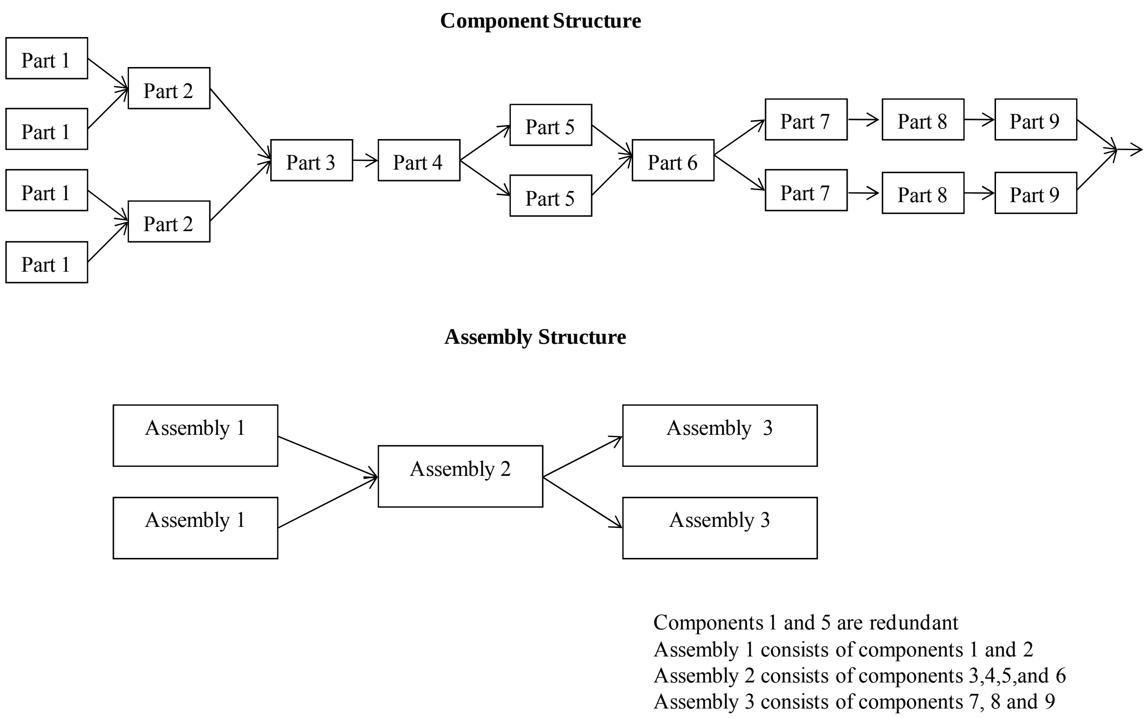

Fig. (4.2): Redundancy bloc diagram (Kaplan, 1989)

Secondly, system redundancy involves that in a system of N enclosure subsystems, not all N subsystems should function for the system to operate correctly. Consequently, only a number of subsystems are needed to operate to ensure system functionality. Within this configuration, support time will have less effect on system availability and, therefore, the probability of a system downtime becomes trivial.

The literature on redundancy problems is quite extensive, but the majority of publications have focused on designing efficient configurations for series-parallel systems. Their utmost objective is reliability maximisation by selecting which parts to use and its related redundancy levels. The mathematical formulation of this problem is solved using integer programming (Bulfin et al., 1985; Gen et al., 1990), dynamic programming (Fyffe et al., 1968; Nakagawa et al., 1981; Ng et al., 2001) and genetic algorithms (Ida et al., 1994; Painton et al., 1995: Coit et al., 1996 and Levitan, 2001). On the other hand, there has been less research directed towards the study of redundancy implication on spare part optimisation. The issue of redundancy in spare part optimisation has been addressed by Sherbrooke (1991), Kaplan (1989) and Smidt-Destombes, et al. (2009). They convert system structure into assembly structure also called a redundancy block diagram as shown in figure 4.2.

4.3.1.3 COMMONALITY

It frequently occurs that different subsystems may share the same subsequent components. This situation is also known as commonality. The reason of incorporating commonality in system design is the consequences in terms of financial benefits. Since physical systems are often structured into more than two indenture levels, it is necessary that inventory model should take into account the effect of commonality in spare part optimisation. The mathematical formulation of such model will be presented in section 4.4.2.

4.4 THE METRIC MODEL

Almost all researches up to now in spare inventory management refer to this Model. It is a mathematical model introduced by Sherbrooke (1968) to determine the optimal inventory levels for service parts for a multi-item two-echelon situation with one central depot and several local bases. Within METRIC model (Multi-Echelon Technique for Recoverable Item Control); the process of spare part provision is described as follows. A demand for spares is originated when installed systems are down due to their item failures. The damaged parts are immediately replaced by new ones if available in stock on hand or repaired at the nearest repair level; otherwise the demand is ordered from the preceding stock level. At the preceding level, the demand will receive the same treatments as those received in the subsequent level. In addition, the METRIC model assumes the following data are known for all items: demand rates, repair times, order and ship times between repair levels and repair probability. Then, it employs a marginal analysis technique to rank all possible increase in spare inventory in terms of the increase in system availability per unit cost. Item leading to the greatest value in system availability per dollar will be put on procurement list. This method is repeated until the system availability reaches 100%, resulting in availability-vs.-cost curve (figure 4.3).

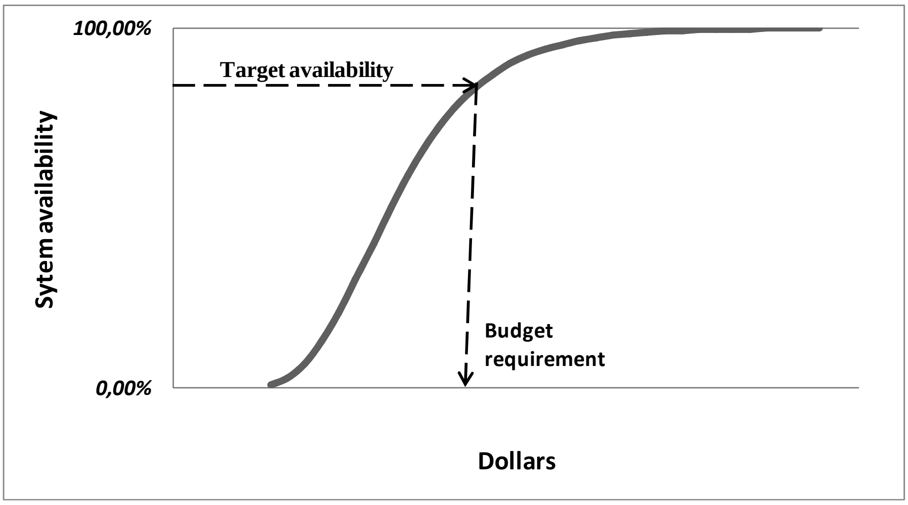

Fig. (4.3): Availability-vs.-Cost Curve

This curve which is a cost-effective spares mixes to maximise system readiness can help asset managers make support budgeting and funding decisions. The METRIC output can be employed in two different ways. Firstly, given an availability target the procurement spare list ensuring the minimal cost mix is developed. Secondly, the METRIC model provides a budget limit beyond which there are no considerable improvements in system availability. This marginal analysis method is recommended to a variety of systems ranging from complex ones such airplanes to a simple ones like pumps. This dominant model for spare part control is based on the following considerations:

1. System: is a group of components that, working jointly, produce its intended function (Maier, et al., 2000). ISO/IEC/IEEE 15288 (2005) defines a system as a physical entity capable of providing services in defined environments. The commonly representation of complex systems is a hierarchical physical structure or organisation consisting of thousands of items. With respect to spare part management, each item in a system is considered only when it has a contribution to the system availability.

2. Indenture: A system is typically arranged into several components; each component includes a number of assemblies that are constituted of items/parts (Fig. 4.2). The system breakdown structure, commonly known as bill of materials BOM, is an item hierarchical organisation in which a layer is called an indenture. The first-indenture components, called generally line repair units LRUs, have a great effect on system availability. When LRUs are available in stock, failed systems are operational almost instantaneously but at very high inventory cost. On the other hand, components at subsequent indentures, called shop replaceable units SRUs, have a limited impact on system availability compared to LRUs. Therefore, the inventory model develops a cost effective balance between procuring LRU and SRU spares.

3. Echelon: within organisations owing a number of systems spread over a huge geographical area, repair service should be structured in a hierarchical network. In such case, spare parts are stored at operating or local bases and at a central depot. The latter supplies all local bases but it takes a shipping or transportation time to arrive. The base stocks are intended to satisfy rapidly on-site demands and in some situation the demands at other locations. The inventory model tries to allocate optimally spare between the central depot and the operating bases with respect to the availability constraint.

4. Repair: failed components are removed from system to be serviced firstly at the nearest local bases. If not reparable there, they are shipped to next higher reparation level to be serviced. This will be repeated until the failed components arrive at the central base. Besides, spare parts may be stored at all echelons and it will be sent down in repair network to replace the reparable items that have been sent up. Repair shop capacity may be considered as infinite where maintenance is supposed to start as soon as a failed item arrives at a repair facility; or it may be limited, where arriving items should queue and wait for service. Basically, system availability is inversely proportional to support time which includes repair time and queuing time. The latter depends on how heavily failed items arrive and on how large the repair capacity is. In practice, installed repair shops may enclose several repair resources, each of which treats defined sets of LRU and SRU types. METRIC labels the movement of component under repair or replacement by pipeline whose mean

time is the delay time for shipment between repair levels and repair time. Besides, METRIC assumes that repair capacity is infinite and therefore the delay time related to queueing at repair shops is ignored.

Finally, the mathematical equations that underpin the METRIC process are detailed in the following subsections.

4.4.1 SINGLE-ECHELON, SINGLE-INDENTURE MODEL

In this section, the model estimates the required stock level for one single repair shop which serves many one-indenture systems. Each of these systems has Z_i parts of item i. When one of these parts fails, the complete system stops working. To reduce system downtimes, spare parts should be available immediately. The METRIC model optimises the stock level based on the following assumptions:

1. All items can be repaired within repair network;
2. Failures are stationary Poisson processes and independent of the number of items under repair;
3. (S – 1, S) inventory policy is applied for all items at all repair bases.
4. The repair time of any item follows an exponential distribution.
5. Each failed item is shipped to the repair base without delay (an infinite number of transporters). The transportation time is known as order-and-ship time.
6. Backorders for different items have the same importance.
7. Repair resources are infinite;
8. When repair is done, all failed items become as good as new.

The notation adopted in METRIC is as follows:

N	number of items;
Z_i	number of occurrences of item i;
i	= {1, 2,...,n} : set of spare parts;
λ_i	demand rate of part i;
S_i	stock level for item i ;
r_i	probability that item i can be repaired at the base;
t_i	mean repair time of part i at the base;

o_i mean transportation time of item i to the base from its supplier (referred also by order-and-ship time)

c_i price of item i

$BO_i(S_i)$ numbers of backorders for item i at the base as function of the stock level S_i;

$PBO_{ij}(S_{ij})$ backorder probability for item i at the base as function of the stock level S_i;

The backorder number, denoted by $BO_i(S_i)$, stands for requested quantities of item i. It is the positive value representing the difference between the needed spare parts of item i, denoted by pipeline P_i, and the stock at hand $S_i$at the base:

$$BO_i(S_i) = [P_i - S_i]^+ = \max(0, P_i - S_i) \tag{4.1}$$

First of all, let us consider the following situation to derive backorder BO expressions. In the case where there are plenty of spares at the base $(S_i \sim \infty)$ to satisfy any demand, there will be no delay. However, at low spare quantities there will be delay time for transportation time (order and receive from the base) plus repair time. Therefore, delay can be expressed as a function of stock level S_i; if the demand P_i is less than S_i there will be no delay but if there are greater thanS_i, then the supply of $(P_i - S_i)$ items will be delayed. The expected number of delayed items or the expected number of backorder may be expressed:

$$BO_i = \sum_{x = S+1}^{\infty} (P_i - S_i) * P(P_i > S_i) \tag{4.2}$$

As a result, for each stock level $S_i$the expected backorders is obtained as a function of the stock level S_i, the demand P_i (pipeline) and its distribution probability $P(P_i > S)$. Under METRIC assumptions, Palm's queuing theorem can be applied. This theorem stipulates:

When failed items arrive according to Poisson process with mean λ and when the repair times are independent and identically distributed random variables with mean t, then the steady state probability distribution for items in repair is a Poisson distribution with mean $\lambda * t$.

Therefore, the probability distributions for a positive backorders of item i is computed as follows:

$$PBO_i(S_i) = P(BO_i > 0) = P(P_i > S_i)$$

$$= \sum_{P_i = S_i + 1}^{\infty} P(P_i = S_i)$$

$$= 1 - \sum_{P_i=0}^{S_i} P(P_i = S_i)$$

$$= 1 - \sum_{x=0}^{S_i} \frac{(\lambda_i * rt_i)^x}{x!} e^{-\lambda_i * rt_i} \quad (4.3)$$

Even though there are diverse methods of calculating system readiness, they all depend on system downtime. System downtime is related to items' support time which includes: awaiting-repair time, in-process time and transport-part time. To evaluate system readiness resulting, the expected length of support time should be calculated. Besides, there is a variety of formulas to measure system readiness (Blanchard, 1998). The well known one, which is widely employed in practice is operational availability (A) defined as:

$$A = \frac{MTBF}{MTBF + MTTR + WT}$$

With:

MTBF: mean time between failure
MTTR: mean time to repair
WT: mean waiting time

In METRIC model, Sherbrooke used the number of backorders BO to measure system availability by the following approximation:

$$A = \prod_{i=1}^{N} (1 - \frac{EBO_i(S_i)}{Z_i})^{Z_i} \quad (4.4)$$

The difference $(1 - \frac{EBO_i(S_i)}{Z_i})$ represents the availability of item i. This difference to the power Z_i represents the availability of a system due to item i. Finally, multiplying over all items (i=1...N) gives the general expression for the availability of the whole system as a result of the stocking policy for service items. Therefore, the probability that the system is not down due to a lack of an item i is $(1 - \frac{EBO_i(S_i)}{Z_i})^{Z_i}$. The above Sherbrooke's formula assumes that the probabilities for different items are independent and the system is a serial structure in reliability terminology. By applying logarithm to A, and considering $\log(1 - \alpha) \approx -\alpha$ for small α, the equation (4.4) becomes:

$$\log(A) = \sum_{i=1}^{N} \left[Z_i * \log\left(1 - \frac{EBO_i(S_i)}{Z_i}\right) \right]$$

$$= -\sum_{i=1}^{N} EBO_i(S_i) \quad (4.5)$$

Equation 4.5 shows that maximising this availability function is approximately equivalent to minimising the sum of the expected backorders. Consequently, the optimisation of spare part inventory will be:

$$
\begin{cases}
\min \sum_{j=1}^{N} \mathrm{EBO_i}\,(\mathrm{S_i}) \\
\text{Subjet to} \\
\mathrm{S_i} \geq 0 \\
\sum_{i=1}^{n} \mathrm{c_i} * \mathrm{S_i} \leq \text{Budget}
\end{cases}
\tag{4.6}
$$

The inventory optimisation objective is to determine inventory policies at bases to minimise spare holding costs while maintaining an average availability greater than a given threshold value. The above mentioned integer programming model requires the identification of steady-state expressions for the expected backorder and stock levels. Sherbrook (1992) has also proposed a greedy-type heuristic method for this problem, which is composed of two steps. The first step is to select the initial spare part mix that backorders curve should be convex. Rustenburg (2000) shows that this greedy method leads to good results when the following initial stock levels are chosen: $\mathrm{S_i} = \max(\lambda_i * t_i - 2; 0)$.With these starting values, backorders will have only positive values and as a result the greedy algorithm can be implemented. Since any increase of stock level represents a decrease in backorder values, a greedy rule consists of increasing at once the stock level for each item by 1, and adding to a procurement list item which offers the highest reduction in the total expected backorders per invested dollar. The second step lies in reiterating the greedy rule until the limit budget or the required availability threshold value is reached. The outcome of this step is a mix of spare part leading to cost-effective investment in inventory stock, represented by the optimal availability vs. cost curve (fig. 4.1).

Summarised, the optimisation algorithm works as follows:

1. Initialise the stocks levels according to $S_i = max(\lambda_i * t_i - 2; 0)$.
2. Set the initial inventory cost $C = \sum_{i=1}^{N} S_i * c_i$
3. Calculate the ratio $\Delta_i = \frac{\sum_{i=1}^{N} EBO(S_i) - \sum_{i=1}^{N} EBO(S_i+1)}{c_i}$
4. Increase the stock by 1 for item which generates the maximum Δ_i
5. Increase the inventory cost C by c_i
6. If $C \leq Budgte\ limit$, then go to Step 3, else STOP

In the same way, this algorithm could be based on a target availability criterion. Instead of the budget restriction (stop criterion in 6), restriction will be set when the system availability becomes greater a target value.

4.4.2 SINGLE-ECHELON, TWO-INDENTURE MODEL

In this section, the previous model is extended to a single-echelon and two-indenture case. The item failure is now the result of the defection of the item itself or one of its enclosure components called children. In studying inventory models, the system breakdown structure depicting item relationship plays an important role in this case. In such a structure, a system is a collection of line replaceable units (LRUs) and each LRU is an aggregation of shop replaceable units (SRUs) which are made up of sub-SRUs, and so on until the last indivisible item. In such a breakdown structure:

- A single item may be considered as a whole LRU.
- Identical items can be located in several indenture levels.

Another central issue in considering system breakdown structure is commonality. Typically, multiple systems may share a number of subsystems or different items and within a same system different items may share some components. If there is no overlap between items with respect to the enclosure parts, inventory, and therefore performance, for the different items will not interfere. Besides, if items have parts in common and no separate stocks are hold for each item, commonality should be considered to obtain a cost-effective inventory pooling.

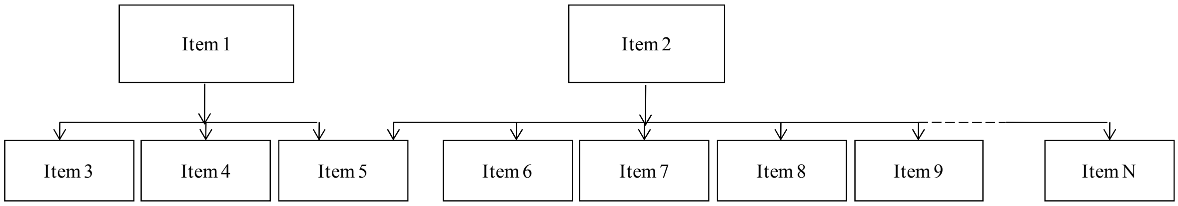

Fig. (4.4): Two indenture system with one common item

This extension permits two types of parts to be considered, a parent and its children. As in previous model, the objective is to determine the base inventory stock levels which maximise the system availability subject to an investment constraint. Similarly backorders are minimised instead of maximising system availability to evaluate the optimal redistribution of stock among system items. Besides, the METRIC model assumes part failure follows a stationary Poisson distribution, repair capacity is unlimited and all failed parts are considered to be repaired. However, the mean difference is the relationship among items and their appearance in system structure. Parts on the first indenture level are called assemblies or parents and they may include a set of children called subassemblies. Subassemblies may share a number of parents due to possible commonality (Fig. 4.4). The probability that a subassembly j is the origin of the failure its parent i is designated by q_{ij}. Evidently, for each parent i we have: $\sum_{j=1}^{children(i)} q_{ij} = 1$. Therefore, the Poisson process describing parent or assembly i failures is the sum of independent Poisson processes for failures of its children.

When the system fails during the time interval (t, t+t_i), the broken item (items) on the first indenture is disassembled and sent into repair shop for reparation. The main feature of this item defection is that it is caused by its children or by the item itself. Therefore, the pipeline P_i (the outstanding demands rising from the repair shop) may be written as:

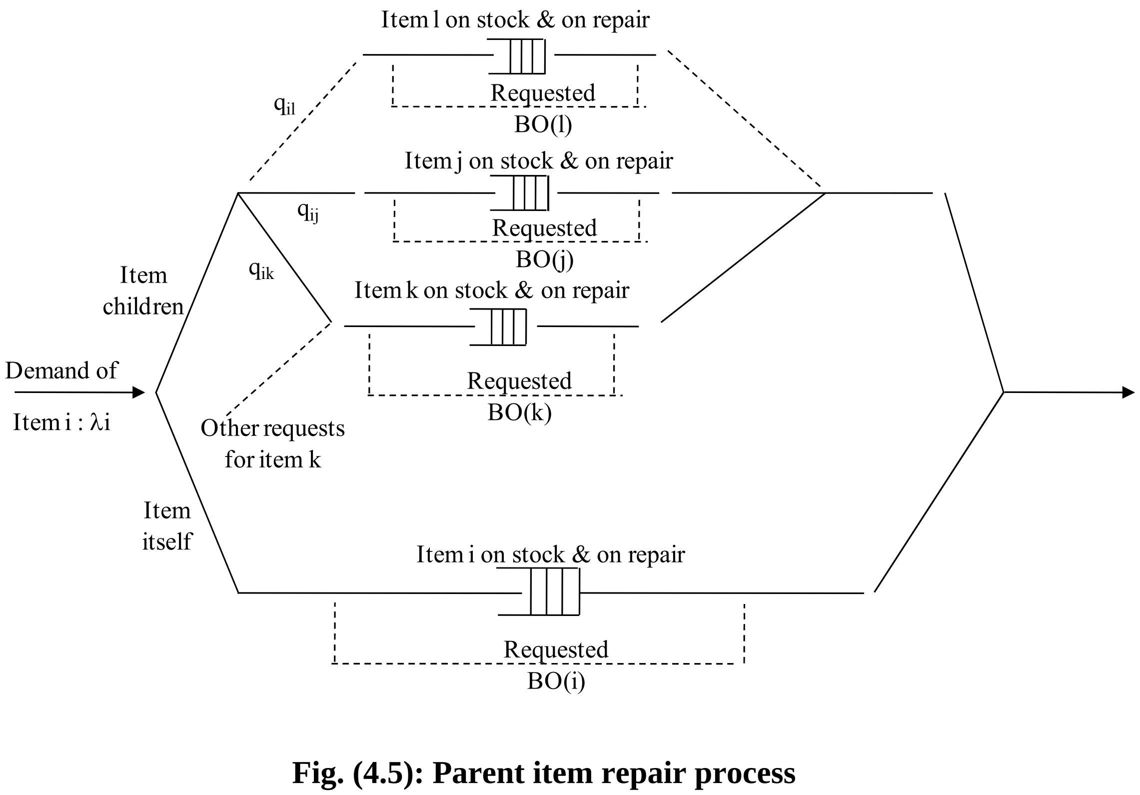

Fig. (4.5): Parent item repair process

$$P_i(t_k) = \text{parent item demand } + \text{parent item requisting demand for its children}$$

The first element on the right-hand side of this equation is the demand for item i, which is assumed to follow Poisson process with rate λ_i and parameter $\lambda_i * t_i$. However, the second element represents the demand of items making up the items i. Their demands are calculated based on parent demand using this equation: $t_j * \lambda_j = t_j * \sum_{p \in parent(j)} \lambda_p * q_{jp}$. Besides, the probability that a request for item j comes from repair of its parent i due to the commonality (same items shared by more than one parent) equals: $h_{ji} = \frac{\text{demand rising from the parent itme i}}{\text{total demand of item j}} = \frac{\lambda_i * q_{ij}}{\lambda_j}$. Therefore, the expected number of items at the repair shop, destined to item j, equals $E[BO_j(S_j)] = h_{ji} * E[BO_i(S_i)]$. Under METRIC process, the backorders for item j that have been originated from failure of item i is binomially distributed with parameters BO_i and h_{ji}.

$$BO_j = \begin{cases} 0 & \text{if } x_i \le S_i \\ BIN(x_i - S_i, h_{ji}) & \text{if } x_i > S_i \end{cases} \tag{4.7}$$

Where:

x_i is the pipeline of item i;

S_i the stock on hand of item i;

BIN: binomial distribution.

The next important step in METRIC model is to identify the expected backorder quantity BO_i for all parts given the quantities S_i. From equation (4.1), expected backorder is written as:

$$\begin{aligned} E[BO_i(S_i)] &= \sum_{S_i+1}^{\infty} (x - S_i) * P(BO_i > 0) \\ &= \sum_{0}^{\infty} (x - S_i) * P(BO_i > 0) - \sum_{0}^{S_i} (x - S_i) * P(BO_i > 0) \\ &= -S_i + \sum_{0}^{\infty} x * P(BO_i > 0) - \sum_{0}^{S_i} (x - S_i) * P(BO_i > 0) \end{aligned} \tag{4.8}$$

Since it is assumed that the demand for parent part i arrives according to Poisson process with parameter $E[DI] = \lambda_i * (r_i * t_i + (1 - r_i) * O_i)$, the equation (4.8) becomes:

$$E[BO_i(S_i)] = E[DI] - S_i - \sum_{0}^{S_i} (x - S_i) * P(BO_i > 0) \tag{4.9}$$

The most general technique to compute the above expected backorder quantity is to approximate the probability $P(BO_i > 0)$ by a discrete distribution fitted on the first two moments as given by Adan et al. (1996). The second moment of backorder quantity is:

$$var[BO_i(S_i)] = E[BO_i(S_i)^2] - E[BO_i(S_i)]^2$$

Where:

$$E[BO_i(S_i)^2] = \sum_{S_i+1}^{\infty} (x - S_i)^2 * P(BO_i > 0)$$

$$= \sum_{0}^{\infty} (x - S_i)^2 * P(BO_i > 0) - \sum_{0}^{S_i} (x - S_i)^2 * P(BO_i > 0)$$

$$= \sum_{0}^{\infty} (x^2 - 2 * x * S_i + S_i^{\ 2}) * P(BO_i > 0)$$

$$- \sum_{0}^{S_i} (x - S_i)^2 * P(BO_i > 0)$$

$$= S_i^{\ 2} - 2 * S_i * \sum_{0}^{\infty} x * P(BO_i > 0) + \sum_{0}^{\infty} x^2\, P(BO_i > 0)$$

$$- \sum_{0}^{S_i} (x - S_i)^2 * P(BO_i > 0)$$

$$= S_i^{\ 2} - 2 * S_i * E[DI] + E[DI]^2 \ - \sum_{0}^{S_i} (x - S_i)^2 * P(BO_i > 0) \tag{4.10}$$

Now, the second moments for subsequent item j is equal to

$$\mathrm{var}[BO_j(S_j)] = E[BO_j(S_j)^2] \ - E[BO_j(S_j)]^2$$

Where:

$$E[BO_j(S_j)^2] = \begin{cases} 0 & \text{if } \ x_i \le S_i \\ h_{ji} * (1 - h_{ji}) * (x_i - S_i) + h_{ji}^2 * (x_i - S_i)^2 & \text{if } \ x_i > S_i \end{cases}$$

$$E[BO_j(S_j)^2] = \sum_{S_i+1}^{\infty} [h_{ji} * (1 - h_{ji}) * (x_i - S_i) + h_{ji}^2 * (x_i - S_i)^2 \,] * P(BO_i > 0)$$

$$= h_{ji} * (1 - h_{ji}) * \sum_{S_i+1}^{\infty} (x_i - S_i) \ * P(BO_i > 0) + h_{ji}^2 * \sum_{S_i+1}^{\infty} (x_i - S_i)^2 \ * P(BO_i > 0)$$

$$= h_{ji} * (1 - h_{ji}) * E[BO_i(S_i)] + h_{ji}^2 * E[BO_i(S_i)^2] \tag{4.11}$$

At the present it is quite simple to derive expressions for the second moment of child item j:

$$\mathrm{var}[BO_j(S_j)] = E[BO_j(S_j)^2] \ - E[BO_j(S_j)]^2$$

$$= h_{ji} * (1 - h_{ji}) * E[BO_i(S_i)] + h_{ji}^2 * E[BO_i(S_i)^2] - h_{ji}^2 * E[BO_i(S_i)]^2$$

$$= h_{ji} * (1 - h_{ji}) * E[BO_i(S_i)] + h_{ji}^2 * \mathrm{var}[BO_i(S_i)]$$

$$= h_{ji} * (1 - h_{ji}) * E[BO_i(S_i)] + h_{ji}^2 * E[BO_i(S_i)^2] \tag{4.12}$$

Recall that the mean pipeline of any item i is made up of items in repair, items in order and ship at the supplier of central depot and items waiting for children replacement. Therefore, the pipeline expression regroups the following three elements:

1. The pipeline of items in repair in which the mean number of items under repair is given by: $\lambda_i * r_i * t_i$; where λ_i is the failure rate of the item i, r_i is the probability that the item i is reparable at the repair shop and t_i is the mean reparation time.
2. The pipeline of items waiting for children replacement is given by $\sum_{j \in child(i)} h_{ji} * E[BO_j(S_j)]$; where $h_{ji} = \frac{demand\ rising\ from\ the\ parent\ itme\ i}{total\ demand\ of\ item\ j} = \frac{\lambda_i * q_{ij}}{\lambda_j}$.
3. The pipeline of items in order and ship at the supplier of central depot is given by: $\lambda_i * (1 - r_i) * O_i$; where $O_i$is the mean order and ship time.

Putting all together, the mean pipeline expression is:

$$E[\mathrm{p_i}] = \lambda_\mathrm{i} * (\mathrm{r_i} * \mathrm{t_i} + (1 - \mathrm{r_i}) * \mathrm{O_i}) + \sum_{j \in child(i)} \mathrm{h_{ji}} * \mathrm{E}[\mathrm{BO_j}(\mathrm{S_j})] \tag{4.13}$$

In the same way, an expression for the variance of the backorders is given by:

$$var[\mathrm{p_i}] = \lambda_\mathrm{i} * (\mathrm{r_i} * \mathrm{t_i} + (1 - \mathrm{r_i}) * \mathrm{O_i}) + \sum_{j \in child(i)} \mathrm{h_{ji}} * (1 - \mathrm{h_{ji}}) * \mathrm{E}[\mathrm{BO_j}(\mathrm{S_j})] + \mathrm{h_{ji}^2} * \mathrm{var}[\mathrm{BO_j}(\mathrm{S_j})] \tag{4.14}$$

These two moments of the numbers of items in the pipeline are used to derive an expression of backorder distribution based on the technique developed by Adan et al. (1996). They have proposed Poisson process, negative binomial or exponential distribution to approximate discrete distribution. For the availability calculations, the backorders of all items at the highest indenture IND(1) are needed as shown in equation (4.15).

$$\log(\mathrm{A}) = \sum_{\mathrm{i} \in \mathrm{IND}(1)} \left[\mathrm{Z_i} * \log\left(1 - \frac{\mathrm{PBO_i}(\mathrm{S_i})}{\mathrm{Z_i}}\right) \right] = - \sum_{\mathrm{i} \in \mathrm{IND}(1)} \mathrm{PBO_i}(\mathrm{S_i}) \tag{4.15}$$

Similarly to the previous section, Equation 4.6 shows that maximising this availability function is approximately equivalent to minimising the sum of the expected backorders. Consequently, the optimisation of spare part inventory will be:

$$\begin{cases} \min \sum_{i \in IND(1)} EBO_i(S_i) \\ \text{Subjet to} \\ S_i \geq 0 \\ \sum_{i=1}^{n} c_i * S_i \leq \text{Budget} \end{cases} \tag{4.16}$$

This is an explicit part of the objective function which seeks to minimise the sum of expected backorders at the highest indenture. The equation (4.10) shows that EBO_i decreases whenever there is an increase of stock level S of item i. Therefore, the problem (4.16) may be solved by using a greedy heuristic method (Skerbrooke, 1968) based on the following steps. First, an initial base stock level is set for each item i. The corresponding expected backorders and investment cost C are computed. Since increase of S leads to a decrease of EBO, the reduction in sum of expected backorder per invested dollar is calculated when only S_i is increased by one. This sum expected backorder reduction per invested dollar is denoted by the $\Delta_i = \frac{\sum_i BO_i(S_i) - \sum_i BO_i(S_i + e)}{c_i}$, where e is a matrix with all elements equal to zero, except for element i which is equal to 1. The increase by one of item i leading to the maximum Δ_i is selected for stock replenishment. In addition, this replenishment will increase the holding stock cost C by ci. This procedure is carried out until the budget is reached.

Summarised, the optimisation algorithm works as follows:

1. Initialise the stocks levels according to $S_i = max(\lambda_i * t_i - 2; 0)$.
2. Set the initial inventory cost $C = \sum_{i=1}^{N} S_i * c_i$
3. Calculate the ratio $\Delta_i = \frac{\sum_{i=1}^{IND(1)} PBO(S_i) - \sum_{i=1}^{IND(1)} PBO(S_i+1)}{c_i}$
4. Increase the stock by 1 for item which generates the maximum Δ_i
5. Increase the inventory cost C by c_i
6. If $C \leq Budgte\ limit$, then go to Step 3, else STOP

4.4.3 TWO-ECHELON, TWO-INDENTURE MODEL

In this section, two-echelon and two-indenture model is considered. The repair network is not limited to one central depot but it includes a central depot and several local shops as illustrated in Fig. 4.6. The local shops serve installed systems which are consisting of a set of items organised in a hierarchical structure of two indentures as studied in the section 4.4.2. When an item fails, it is removed and replaced by a spare one from the nearest local repair shop, if spare part is available. Otherwise, the part is backordered and the failed system has to wait until a part becomes available at the shop. Besides, the failed part is either repaired at local shop if it is possible or shipped to the next higher repair echelon for repair. This repair and spare provision policy is applied to all shops in repair network.

In METRIC technique, unlimited repair capacity is assumed to deliver an optimal spare part provision throughout the repair network. The focus is devoted to storage decisions in a multi-echelon repair structure and for multi-indenture system arrangement (fig. 4.6). The technique assumes that a system availability constraint is imposed to identify spare provision budget required for each item. Besides, it is assumed that item failures follow the Poisson distribution.

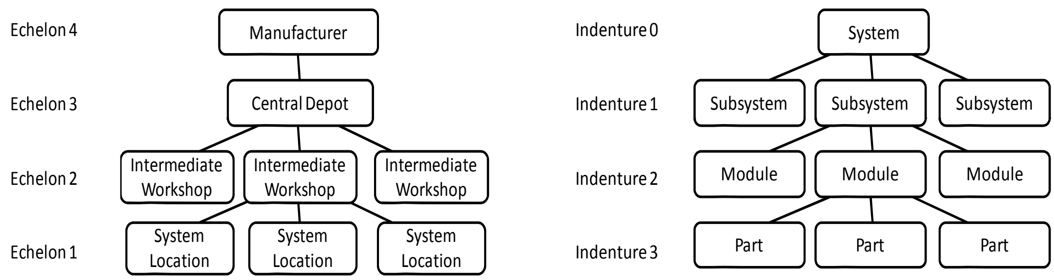

Fig. (4.6): A multi-echelon repair network and a multi-indenture system

Consider the process depicted in figure 4.7. The number of items in the pipeline is the sum of the number of items waiting a necessary spare part plus the number of items in the repair process. In the multi-echelon case, the availability of stock at the central that may be requested by the local repair shops while in the two-indenture case, the available stock of some items that may be required for the repair of the various other items called parent. Therefore, the same line of reasoning as in section 4.4.2 is followed.

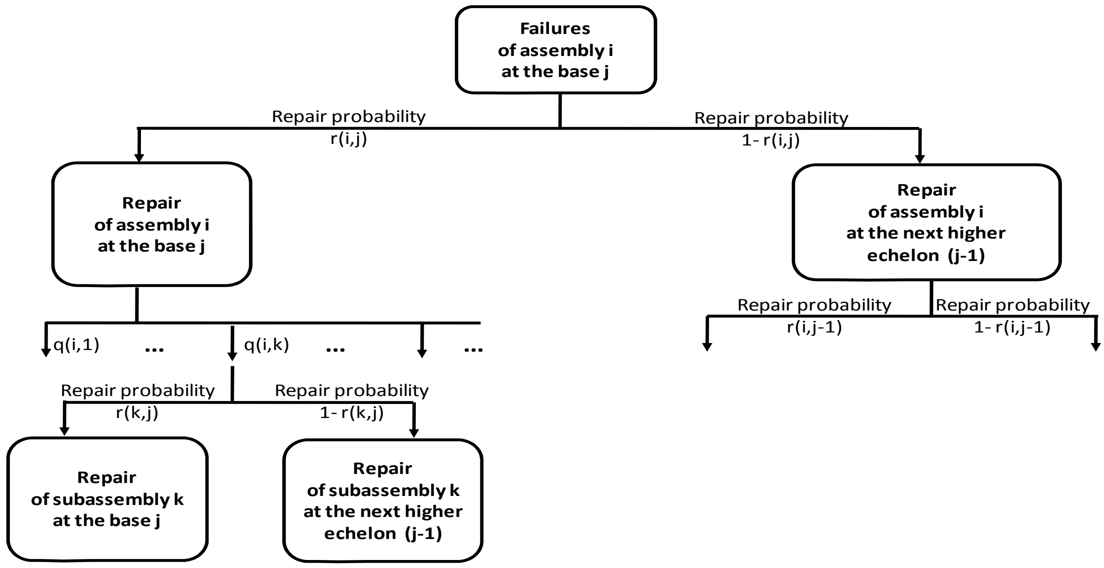

Fig. (4.7): A multi-echelon repair network process

The failure rate $\lambda_{i\,j}$ of item i at base j is computed by adding the following two values (figure 4.7):

1. The failure rates of this item at downstream bases at which repair actions could not be done $\sum_{base\ l>j} \lambda_{i\,l} * (1 - r_{i\,1})$: where $r_{i,j}$ is the probability that an item i could be repaired at base j.
2. The failure rates of higher indenture items: $\sum_{k=1}^{parent\ i} q_{k\,i} * \lambda_{k\,l} * r_{k\,j}$ where : $q_{k\,i}$is the probability that item k is the cause of the failure of its parent i and $r_{k\,j}$: the probability that an item k could be repaired at base j.

Hence, the failure rate of any item i will be:

$$\lambda_{i\,j} = \sum_{\text{base } l>j} \lambda_{i\,l} * (1 - r_{i\,1}) + \sum_{k=1}^{\text{parent } i} q_{k\,i} * \lambda_{k\,j} * r_{k\,j} \tag{4.17}$$

Starting by the highest indenture items, all failure rates can be calculated recursively. The demand quantities or pipeline for the bases are computed according to METRIC assumptions. That is, the repair time and order and ship time from the higher bases are independent and both follow Poisson distribution with parameters $\lambda_{i\,j} * t_{i\,j}$ and $\lambda_{i\,j} * O_{i\,j}$. The pipeline of item i at base j will be therefore the superposition of the mean of these two Poisson distributions multiplied by respective probabilities. As a result:

$$P_{i\,j} = \lambda_{i\,j} * rt_{i\,j} * r_{i\,j} + \lambda_{i\,j} * O_{i\,j} * (1 - r_{i\,j}) \tag{4.18}$$

From Equation (4.18), it is easy to notice that the pipelines should be extended to take into account pipeline from both higher bases and higher indentures. Only a fraction of the pipeline at base j suppliers originates from base j. As considered in the literature, orders are filed in First Come First Served basis. Consequently every order has a probability $f_{i\,j} = \frac{\lambda_{i\,j} * (1-r_{i\,j})}{\lambda_{i\,sup\,(j)}}$ to originate from base j (sup(j) stands for supplier of the level j). Then the number of orders that stems from base j, equals $f_{i\,j} * BO_{i\,sup\,(j)}$. Pipeline expression generated from higher indentures is derived as follow: Let us consider an item k for which j is a parent. Only a fraction $h_{i\,j\,k} = \frac{r_{k\,j} * \lambda_{i\,j} * q_{i\,k}}{\lambda_{k\,i}}$ of the backorders for item k at location j is arising from item j. Then, the mean value of pipeline generated from higher indenture of item j equals : $\sum_{k \in SA(j)} (h_{i\,j\,k} * BO_{k\,j})$. Putting all together, the pipeline of item i at base j can be written as:

$$P_{i\,j} = \lambda_{i\,j} * rt_{i\,j} * r_{i\,j} + \lambda_{i\,j} * O_{i\,j} * \left(1 - r_{i\,j}\right) + f_{i\,j} * BO_{i\,sup(j)} + \sum_{k \in SA(j)} (h_{i\,j\,k} * BO_{k\,j}) \tag{4.19}$$

The equation (4.19) may be interpreted as follows. The term $\lambda_{i\,j} * O_{i\,j} * \left(1 - r_{i\,j}\right)$ represents the part of pipeline due to the transportation process between bases; the terms $\lambda_{i\,j} * t_{i\,j} * r_{i\,j}$ and $f_{i\,j} * BO_{i\,sup\,(j)}$ denote the part that is delayed due to a lack of stock at base j and its supplier echelons and finally the term $\sum_{k \in SA(j)} (h_{i\,j\,k} * BO_{k\,j})$ refers also to the lack of stock of higher enclosure indentures at base j. From equations (4.2) and (4.19), we noticed that the expected backorder is computed from pipeline values and the latter are calculated from expected backorder values. As a result, backorders are computed recursively.

For a given base stock S, evaluation of the steady state backorder probabilities can be done as described in (Rustenburg, et al., 2001), by fitting discrete distribution on the first two backorder moments, e. i expected value and variance. In METRIC, it is assumed that the variance equals the expected backorder of items in repair process, however several researchers have noticed that variance to mean ratio is no longer equals to 1 such under Poisson distribution, but it is usually greater than 1 in practice. Slay (1984) and Graves (1985) developed an approximation for backorder probabilities by applying binomial distribution and the negative binomial distribution respectively. In this study, the approximation is obtained by Poisson, Negative Binomial or Geometric distributions as described by Adan et al (1996). Similar to the expression for the expected backorders, the variance equals to (Skerbrooke, 1968):

$$\begin{aligned} \mathrm{Var}_{\,i\,j} = \lambda_{i\,j} * \mathrm{rt}_{i\,j} * \mathrm{r}_{i\,j} + \lambda_{i\,j} * \mathrm{O}_{i\,j} * \left(1 - \mathrm{r}_{i\,j}\right) + \mathrm{f}_{i\,j} \\ * \left(1 - \mathrm{f}_{i\,j}\right) * \mathrm{BO}_{i\ \mathrm{sup(j)}} + \mathrm{f}_{i\,j}^{2} * \mathrm{var}(\mathrm{BO}_{i\ \mathrm{sup(j)}}) \\ + \sum_{k \in SA(j)} (\mathrm{h}_{i\,j\,k} * \left(1 - \mathrm{h}_{i\,j\,k}\right) * \mathrm{BO}_{k\,j} + \mathrm{h}_{i\,j\,k}^{2} * \mathrm{var}(\mathrm{BO}_{k\,j})) \end{aligned} \tag{4.20}$$

Finally, expression of the Expected Backorders (EBO) as the measure of system performance is given by the following equations:

$$\begin{aligned} E[\mathrm{BO}_{i\,j}] &= \sum_{x\,=\,S\,+\,1}^{\infty} (x - S) * P(x > S) \\ &= \sum_{x=0}^{\infty} (x - S) * P(x > S) - \sum_{x=0}^{S} (x - S) * P(x > S) \\ &= \sum_{x=0}^{\infty} x * P(x > S) - S - \sum_{x=0}^{S} (x - S) * P(x > S) \\ &= P_{i\,j} - S - \sum_{x=0}^{S} (x - S) * P(x > S) \end{aligned} \tag{4.21}$$

For the availability calculations, the backorders of all items at the highest indenture IND(1) and at a downstream location ECH(N) are needed as shown in the following equation.

$$\log(A) = \sum_{i \in IND(1)} \left[Z_i * \log\left(1 - \frac{PBO_i(S_i)}{Z_i}\right) \right] \tag{4.22}$$

Sherbrooke's formula assumes that the probabilities for different items are independent and the system is a serial structure in reliability terminology. By taking the expectation of (4.22), the average availability of all systems at downstream repair base ech(N) is:

$$A = 1 - \frac{1}{ech(N)} \sum_{i=1}^{ech(N)} \sum_{j=1}^{ind(1)} BO_{ij}\,(S_{ij}) \tag{4.23}$$

The spare part management objective is to determine inventory policies at bases to minimise spare holding costs while maintaining an average availability greater than a given threshold value. Sherbrooke shows that maximising this availability function is approximately equivalent to minimising the sum of the expected backorders. Consequently, the optimisation of spare part inventory will be:

$$
\begin{cases}
\min \sum_{i=1}^{ech(N)} \sum_{j=1}^{ind(1)} BO_{ij}\left(S_{ij}\right) \\
\text{Subjet to} \\
S_{ij} \geq 0 \\
\sum_{i=1}^{n} c_i \sum_{j=1}^{ech(N)} S_{ij}
\end{cases}
\tag{4.24}
$$

The stock allocation is obtained by using the following iteration algorithm:

- **Step 0**: since the optimisation procedure of the problem (4.24) is a greedy heuristic, a prerequisite of this procedure is the function backorder BO against the cost C should be convex. Rustenburg et al., (2002) have examined the effect of initial stock on the curve convexity and they found that this stock should be set equal to $S_{i\,j} = \mathrm{round}\left(\lambda_{i\,j} * t_{i\,j} * r_{i\,j} + \lambda_{i\,j} * O_{i\,j} * \left(1 - r_{i\,j}\right)\right)$ and $S_{i\,0} = \mathrm{round}\left(\lambda_{i\,0} * t_{i\,0} * r_{i\,0} + \lambda_{i\,0} * O_{i\,0} * \left(1 - r_{i\,0}\right)\right)$ at the depot base.
- **Step 1:** Stock level S_{ij} is increased by 1.
- **Step 2:** The mean and the variance of pipeline value are calculated.
- **Step 3:** Fit a discrete distribution to mean and variance of pipelines assuming that their constituents are uncorrelated.
- **Step 4:** the expected numbers of backorders $BO(S_{ij})$ are calculated.
- **Step 5:** the quotients $\Delta_{i\,j}$ is calculated
- **Step 6:** the pair (i,j) leading to the highest value of $\Delta_{i\,j}$ is selected.
- **Step 7:** Stock level $S_{i,j}$ is increased by 1 for the selected (i,j)
- **Step 8:** if the criterion stock cost $C \leq$ budget is satisfied then go to step 1, otherwise stop.

4.5 THE METRIC LIMITATIONS

As stated above, the first version of metric model was single echelon, single indenture model. Afterwards, there have been several lines of research on enhancing METRIC outputs. One line pertains to add some features to METRIC model to tackle some practical issues. On the basis of the previous model, Muckstadt (1973) presented the MOD-METRIC to analyse two-indenture systems instead of single indenture ones. Moreover, Slay (1984) proposed VARI-METRIC model where the hypothesis of the equality of backorder mean and variance are no longer assumed. Moinzadeh et al. (1986) have delivered a decision tool to select an (S - 1, S) policy versus an (r, Q) policy. Their tool was tailored only to multi-echelon inventory systems with a single indenture. In addition, Axsater (1990) has optimised inventory base stock levels by determining average holding and shortage costs. The common characteristic of these researches is they have focus only of spare part inventory.

In addition, the formulation of the METRIC models is based on a set of assumptions. The most important assumption considers that the repair capacity is unlimited, i.e. there is no waiting time for a repair. Therefore, the repair times for failed items at all repair shops are independent and identically distributed random variables with a given mean for each item. In all METRIC models reviewed hitherto repair capacity is assumed ample which is often an unrealistic in real-world contexts. In industrial setting of spare part inventory analysis, each repairable failed item is supplied to repair shop where reparation time encompasses generally waiting time for repair and repair time (figure 4.8). A serious limitation of the previous models is that they work under the assumption that both waiting time and repair time are constants and independent for each component, i.e. the repair capacity is infinite. Due to budget constraints, companies invest a certain amount in repair facilities to guarantee a predefined level of maintenance performances and therefore infinite repair capacity is seldom realistic. This causes an underestimate in spare parts to maintain target availability above a predefined threshold value. Díaz et al., (1997) were the first who studied spare part management under limited repair facilities. They consider the situation where all failed items are repaired only at the central level which has a limited capacity. Their approximation for the repair time was based on queuing theory. Unfortunately, they derived model equations only for a single-server multi-class queue model due to analytical complication. Sleptchenko et al. (2002, 2005) extended the previous work by studying a more general multi-class multi-server queuing model. However, to deliver an analytical solution, they limit themselves to steady state for a given repair capacity.

Based on this review, extensive research has been devoted to the fields of inventory location theory, queuing theory and level of repair analysis; yet research that establishes the interaction of these fields is limited. Since this research deals with the spare part management and in particular, it focuses on the interaction between spare part provision and repair capacity. Its outcome will be a framework to support policy and decision-makers model that simultaneously considers a multi-echelon repair network with inventory pooling, level of repair analysis and finite repair capacity for multi-indenture systems.

4.6 FINITE REPAIR CAPACITY

The underlying assumption in the above model is that repair capacity is infinite and as a result, the repair shops are not considered as a decision variable. Díaz, et al. (1997) first relaxed this assumption by considering limited repair facilities only at the central base. Other researchers tried to extend the METRIC method to study the impact of finite capacity (Aboud,1996; Sleptchenko et al., 2002 and Kim et al. 2000). They have shown that limited capacity has a considerable effect on system performance for a single indenture and one or two-echelon repair network.

On the other hand, queuing theory has been the solution for range of practical problems in telecommunication, manufacturing and computer systems. Then, it is obvious that the more suitable way to manage spare parts considering also queuing network approach. There is an extensive literature on queuing theory (Gross, et al., 1983; Gross, et al., 1998; Whitt, 1993; van der Heijdena, et al., 2004 and Bhat, 2008). The M/G/K queuing system is one of the most used models for multi-server systems. The symbol M means that the jobs arrive according to a Poisson process with rate λ; the symbol G assumes that service time is independent and identically distributed random variables having a general distribution and K refers to the number of identical servers working with a First-Come-First-Serve (FCFS) policy. Any job received immediately service only when a free server exists, otherwise it waits in the FCFS queue.

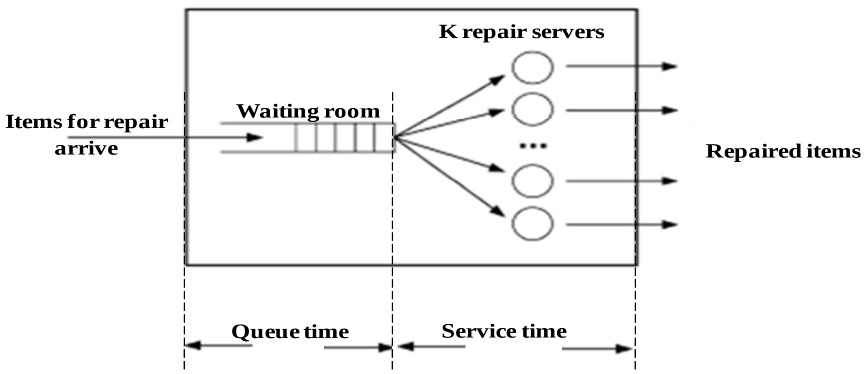

Fig. (4.8):Repair time components

In practice, repair shops are generally run by a limited quantity of equipment and multi-skilled crew that are able to handle at the same time a certain number of repair jobs. This gives rise to multi-server configuration, where failed items arriving with Poisson process are either in the queue or in service (figure 4.6). Therefore, failed items in repair shops are modelled using M/G/K queuing theory. The mean and variance of the number of items in the repair shops are given by the following approximations based on (Whitt, 1983, 1993):

$$E(N) = \lambda * \left[\left(\frac{1 + C^2}{2}\right)\left(\frac{p_0}{k * \mu}\frac{(k * \rho)^k}{(1 - \rho)^2 * k!}\right) + \frac{1}{\mu}\right] \tag{4.25}$$

$$V(N) = E(N^2) - E(N)^2 \tag{4.26}$$

Where:

$$E(N^2) \approx E\left(N^2_{M/M/K}\right) * \frac{E(N)^2}{E(N_{M/M/K})^2} \tag{4.27}$$

$$E\left(N_{M/M/K}\right) = k * \rho + \frac{\rho * (k * \rho)^k}{(1 - \rho)^2 * k!} p_0 \tag{4.28}$$

$$E\left(N^2_{M/M/K}\right) = k * \rho * \left(1 + \frac{(k * \rho)^k}{(1 - \rho) * k!} p_0\right) + \frac{\frac{(k*\rho)^k}{(1-\rho)*k!} p_0 \left[1 + \rho * \left(1 - \frac{(k*\rho)^k}{(1-\rho)*k!} p_0\right)\right]}{(1 - \rho)^2} + E(N_{M/M/K})^2 \tag{4.29}$$

Where:

$$p_0 = \left[\sum_{j=0}^{k-1} \frac{(k * \rho)^j}{j!} + \frac{(k * \rho)^k}{(1 - \rho) * k!}\right]^{-1}$$

k number of servers at the repair shop,

μ service rate of each server,

λ_i arrival rate of failed item i,

$\lambda = \sum \lambda_i$ arrival rate at the repair shop,

$\rho = \frac{\lambda}{k*\mu}$ utilization of the repair shop,

S service time at the repair shop, $E(S) = \frac{1}{\mu}$

N number of items at the repair shop,

Q number of items in queue at the repair shop,

W waiting queue time at the repair facility,

C, coefficient of variation for random variable $C = \frac{\text{Varaince}}{\text{mean}^2}$

P_n Probability that there are n items at the repair shop.

These first two moments concern only items under repair service, however, the repair time includes as well the waiting time in the queue when servers are full. The waiting time is, in turn, presented by another random variable $Q^{+} = \mathrm{Q/Q} > 0$ (the conditional queue length given that the queue is not empty). Its mean and variance are given by:

$$E(Q^{+}) = \mathrm{E(Q)/p(Q > 0)} = \left[\mathrm{E(N)} - \frac{\lambda}{\mu}\right] / \mathrm{p(Q > 0)} \tag{1}$$

Where :

$$\mathrm{p(Q > 0)} \approx \rho * \mathrm{p(W > 0)} = \rho * \min(\pi, 1)$$

$$\pi = \rho^2 * \pi_a + (1 - \rho) * \pi_b$$

$$\pi_a = \min\left\{1, \frac{1 - \Phi\left(\frac{(1+C_s^2)*(1-\rho)\sqrt{k}}{C_a^2+C_s^2}\right)}{1 - \Phi\left((1-\rho)\sqrt{k}\right)} \mathrm{p}\left(W_{M/M/K} > 0\right)\right\} = \mathrm{p}\left(W_{M/M/K} > 0\right)$$

$$\pi_b = \min\left\{1, \frac{1 - \Phi\left(\frac{2(1-\rho)\sqrt{k}}{1+C_s^2}\right)}{1 - \Phi\left((1-\rho)\sqrt{k}\right)} \mathrm{p}\left(W_{M/M/K} > 0\right)\right\}$$

$$\mathrm{p}\left(W_{M/M/K} > 0\right) = \rho$$

$\Phi(\dots)$ is a cumulative function of standard normal distribution

The term π_a is equal to $\mathrm{p}\left(W_{M/M/K} > 0\right) = \rho$ since arrival time is assumed to be a Poisson process for which mean^2 = variance $= \lambda^2$ and the coefficient of variation $C = \frac{\text{Varaince}}{\text{mean}^2} = 1$.
The variance of waiting time Q can be obtained by computing its coefficient of variation C_{Q^+} :

$$\begin{cases} C_{Q^+}^2 = \dfrac{1}{E(Q^+)} - \dfrac{\mathrm{p(Q > 0)}}{\mathrm{p(W > 0)}}(C_D^2 + 1) \\ C_D^2 = 2 * \rho - 1 + 4 * (1 - \rho)\dfrac{d_s^3}{3 * (C_s^2+1)^2} \\ d_s^3 = \begin{cases} 3 * C_s^2 * (C_s^2 + 1) & if C_s^2 > 1 \\ (2C_s^2 + 1) * (C_s^2 + 1) & if C_s^2 < 1 \end{cases} \end{cases} \tag{4.30}$$

Finally, backorders given by equation (4.21) can be approximated based on the first two moments of the numbers of items in the pipeline. The common technique to obtain this is set by Adan et al. (1996). Based on this approximate, the probability distribution for the pipeline P(X>0) is fitted on the first two moments of negative binomial, Poisson or mixed two geometric distribution.

4.7 THE ALGORITHM FOR CALCULATING OPTIMUM SPARE PART INVENTORY

On the basis of the above mathematical expressions, the optimisation algorithm has been defined as the maximisation of the quotient of the backorders BO to cost increment, i.e., $\Delta_{i\,j} = \frac{\sum_i \sum_j BO_{i\,j}(S) - \sum_i \sum_j BO_{i\,j}(S+e_{i\,j})}{c_i}$. This criterion function is followed during each iteration step made for identifying the spare part which should be added to the stock. The constraint is that the total cost of spare does not exceed the allowed budget.

The algorithm provides efficient solutions $S_{1,0}$, $S_{2,0}$, $S_{3,0}$, …, S_{ij}, … at all repair shops and for all system enclosed items. Throughout the algorithm S_{ij} denotes generated efficient solution for the item i at the echelon j, $C(S_{ij})$ stands for the corresponding spare part cost and $BO(S_{ij})$ refers to the corresponding expected number of backorders. The algorithm ends when there is no longer any efficient solution with $C \leq$ budget. The stock allocation is obtained by using the following iteration algorithm:

- **Step 0:** since the optimisation procedure of the problem (3) is a greedy heuristic, a prerequisite of this procedure is the function backorder BO against the cost C should be convex. Rustenburg et al;, (2002) have examined the effect of initial stock on the curve convexity and they found that this stock should be set equal to $S_{i\,j} = round\left(\lambda_{i\,j} * t_{i\,j} * r_{i\,j} + \lambda_{i\,j} * O_{i\,j} * \left(1 - r_{i\,j}\right)\right)$ and $S_{i\,0} = round\left(\lambda_{i\,0} * rt_{i\,0} * r_{i\,0} + \lambda_{i\,0} * O_{i\,0} * (1 - r_{i\,0})\right)$ at the depot base.
- **Step 1:** Stock level S_{ij} is increased by 1.
- **Step 2:** the expected numbers of backorders $BO(S_{ij})$ are calculated.
- **Step 3:** The mean and the variance of waiting time and service at repair shop are calculated.
- **Step 4:** The mean and the variance of pipeline value are calculated.

- **Step 5:** Fit a discrete distribution to mean and variance of pipelines assuming that their constituents are uncorrelated.
- **Step 6:** the expected numbers of backorders BO(S_{ij}) are calculated.
- **Step 7:** the quotients $\Delta_{i\,j}$ is calculated
- **Step 8:** the pair (i,j) leading to the highest value of $\Delta_{i\,j}$ is selected.
- **Step 9:** Stock level S_{ij} is increased by 1 for the selected (i,j)
- **Step 10:** if the criterion stock cost C ≤ budget is satisfied then go to step 1, otherwise stop.

For each generated solution S_{ij} is different from the previously generated solution in just one component. $\Delta = \frac{\Delta \text{BO}}{\Delta \text{C}} = \frac{\text{decrease in BO}(S_{i,j})\text{if } S_{i,j} \text{ is increased by 1}}{\text{increase in C}(S_{i,j}) \text{ if } S_{i,j} \text{is increased by 1}}$. Therefore, in each of the above steps, the increase the stock $S_{i,j}$ by 1 should generate marginally the largest decrease of BO(S) per invested dollar.

4.8 SUMMARY

This chapter has reviewed the work done so far in the area of spare part provision. Firstly, it has been devoted to overview theoretical formulation of various inventory models. Then, algorithms for computer application have been presented. Afterwards, a literature review from practical implementation point of view has been discussed; where the ample repair capacity assumption has been considered as mean limitation of spare part models. More specifically, a multi-echelon repair network including a central depot and many field bases has been considered in this chapter. It has been demonstrated that the queuing theory could provide an opportunity to better estimate the required spare parts and especially if the repair shops have a limit capacity. The spare part models under limited capacity investigate the trade-off between the spares inventory and investment in repair facilities. In an intensive system industry like petroleum industry, it may be a worthwhile policy to reduce inventory costs through adequate investment in repair capacity.

The crucial issues that have been covered in this chapter are multi echelon repair network, multi indenture system and limited repair capacity. These issues will be used in next chapters with LORA algorithm to build up the effective support decision framework.

CHAPTER 5 RESEARCH METHODOLOGY

5.1 INTRODUCTION

The previous two chapters have provided a critical review of basic concepts and approaches of Level of Repair Analysis LORA and Spare Parts Inventory Control techniques. The literature has identified the issues indispensable to enhance these techniques in maintenance decision making tool within petroleum industry. In this chapter, a research methodology is outlined and, in particular, the choice the research strategies and approaches appropriate to this study questions and objectives. It will briefly highlight the research process regarding the requirements of combined problem of LORA and spare parts stocking.

In the following section, a variety of approaches and strategies of research methodology are critically reviewed, with focus on the suitability of these approaches and strategies with research aim. Then, issues dealing with reliability and validity related to the research are examined. This is followed by a discussion of data requirements, collection and analysis with emphasis on characteristics and sources of these data. Finally, the main findings of the chapter are summarized. This research work focuses on providing efficient decision tools in the field of system operation management and in particular optimal decisions related to maintenance supportability as defined by integrated logistics support technique. The intended outcome of the research study is formulated in Chapter 1 as: "*To develop a framework by integrating level or repair analysis and spare part inventory control that enables successful maintenance supportability decisions*".

The literature overview has shown that companies that employ complex systems need to enhance their system availability by assuring effective and efficient maintenance services. Therefore, it is important to consider level of repair analysis and spare part inventory control which constitute the bulk of repair time and maintenance support costs. The proposed framework resulting from this research is expected to deliver computer-based tool that can support the business as a whole as well as asset managers and maintenance engineers.

5.2 RESEARCH STRATEGY & APPROACH

The research methodology consists in delimiting the study, dictating the choice of hypothesis and research strategy to address the research questions, arranging results to enable analysis, and the drawing of conclusions that can contribute to the expansion of knowledge. According to Leedy (1993) research is a methodical approach of resolving problems to gain knowledge of a phenomenon. Research may be classified basic research or applied research. The main objective of basic research is to advance general knowledge, whereas applied research is performed to seek solutions of precise problems. Moreover (Bless et al., 1995; Neuman, 2003) state that the major purpose of basic research is to generate new theory while applied research outputs, by contrast, aim at tailoring knowledge to address practical problems of immediate concern. Consequently, researchers use applied research to understand the problem in more detail and a practical investigation was needed to generate new knowledge with regard to solving the problem.

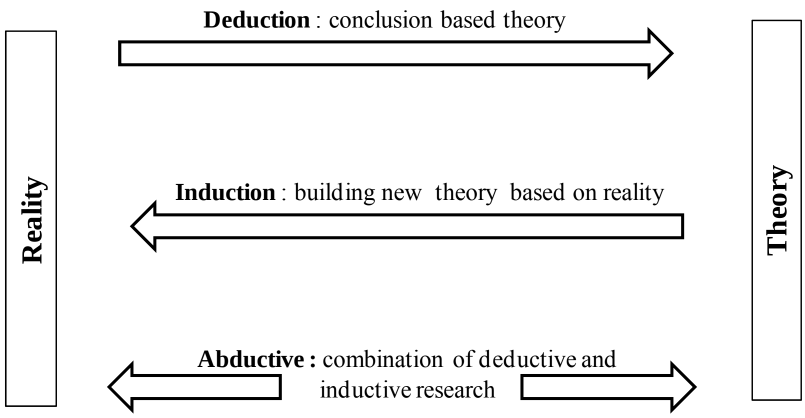

Fig. (5.1): Theory and reality based research approaches (Patel et al., 2003)

Considering the research question of this study, it is to be oriented towards applied research class. This choice is underpinned by fact that the study employed experimental knowledge and offers useful solutions for spare parts inventory control to guarantee system availability and at the same time to avoid lack of spare parts when they are requested. Besides, the petroleum industry suffers from the shortage of spare parts for systems that are generally spread throughout huge geographical areas. This research presents a practical approach for spare parts shortage.

Besides, the two significant research approaches to study a phenomenon are quantitative and qualitative research (Creswell, 2005 and Leedy, 1993). Cresswell (2005) argues that a quantitative research entails specifying questions to answer, gathering numeric information, studying these data and performing the research with pre-defined assumptions. Consequently, quantitative research is mainly a deductive process that can describe, predict and explain a research phenomenon (Locke et al., 1998). More precisely, quantitative methods are statistical analysis methods that can contribute to the understanding of the research phenomenon where researcher can generalise and predict conclusions based on the use of tools such as case studies and questionnaires. However, qualitative research is typically conducted to answer questions about describing and understanding phenomenon from the perspective of the interviewers' point of view.

In social or human science, qualitative research is concerned with the interpretation of the results from participant experiences in order to get possible explanations of the theory or to generalise that the theory hold true' (Creswell, 2005 and Ary et al, 2002). Moreover, several researchers (Huberman, 1994; Yin, 1993 and Emory et al, 1991) state that quantitative research is employed to investigate causal relationships between certain variables under study. On the opposite side, they argue that qualitative research focuses on phenomenon description in a rational manner without measuring cause and effect relationships of variables.

In this research study, a quantitative research approach will be applied. The research is intended to examine the existing issues facing spare part inventory control with regard to petroleum industry. In previous chapters, it has been argued that this research will eventually lead to the development of a tool that will optimise maintenance support decisions. The approach was to start from reviewing support techniques throughout the industries (Chapters 2 to 4) to build up the proposed framework models (Figure 5.5). Their relevance and practical application will be validated on three levels: laboratory level, panel of maintenance experts and finally through case studies. In the state of the art part, several researchers have come to the conclusion that the optimisation of the level of repair analysis LORA and spare part inventory control with limited repair facilities will lead to efficient maintenance decisions. In addition, the lack of published researches on maintenance supportability in petroleum industry leads therefore to analyse the importance of those techniques that affect petroleum equipment maintenance supportability decision-making. The research process will consist of three distinctive phases that aim to identify and determine the importance of factors that affect maintenance supportability decision-making in Algerian petroleum industry.

As mentioned above, research methodology entails a selection of research strategy, a choice to employ histories, archival analysis, surveys, experimentation or case studies. According to Yin (1994), the research strategy choice should be based on information the researchers is looking for within the purpose of the study. He defines five different research strategy classes with regard to the research questions (Table 5.1).

Table (5.1): Research strategy selection (Source: Yin, 1994)

Strategy	**Research question**
History	How, why
Archival analysis	Who, what, where, how many, how much
Experiment	How, why
Case study	How, why
Survey	Who, what, where, how many, how much

Even though other researchers have pointed out that research strategy should depend on a number of factors such as: the control an researcher has over actual behavioural events and the focus on contemporary or historical events (Rowley, 2002), but all of them agreed that research question is the most important in selecting the most suitable research strategy. History and archival analysis focus on questions to investigate past conditions of the phenomenon under study. The other strategies (experiments case studies and surveys) study in general contemporary situation, as defined below:

- Yin (1989) defines the case study approach as follows: "*A case study is an empirical inquiry that investigates a contemporary phenomenon within its real life context*". The case studies are methods that carry out a detailed and profound research to answer how and why questions. The researcher chooses meticulously a few pilot cases to examine some topics in detail analytically rather than use an enumerative induction (Neuman, 2003).
- Experiments, considered as the most valuable method for explanatory research, study a phenomenon in a laboratory or in a real life experimental

setting. They usually deal with a quite small number of cases and handle a precise question in order to better understand the phenomena.

- Surveys, often employed in descriptive or explanatory research, uses data collected from a number of organisations or interviewers by means of questionnaires over a short time period, and then present the answers in graphs and tables. The mean output of surveys is a picture of the issues of interest under the present situation.

Based on the above definitions, experiment & case study methodologies were selected as the most appropriate strategy for answering the research questions. Scientific theories & techniques (Integrated Logistics Support ILS) will be applied in the real life of equipment/systems to identify some of additional features with regard to spare parts inventory optimisation. In addition, the study findings will be investigated in terms of some case studies to increase the understanding of the spare parts management and to allow coming analysis and discussion.

5.3 RELIABILITY AND VALIDITY

This section verifies the integrity of research in terms of validity and reliability. The adopted research design should minimise or eliminate the criticisms for the lack of methodological rigour (Yin; 1994). Based on these criticisms, several authors have set a number of methodologies that should be fully considered by researchers in order to demonstrate the contribution of the research to the knowledge base of a field of study (Rowley, 2002). Reliability, defined by Neuman (2000) as "*dependability or consistency of the measure of a variable*", implies that a reliable instrument will lead to comparable findings when applied repeatedly. In contrary, validity refers to what extent instruments measure precisely what they supposed to measure.

In the field of empirical analysis research, the value of any piece of research depends mainly on the measurement quality. The reliability in quantitative research entails that the numerical results do not differ because of features of the measurement methods or the measurement instrument itself. Its aim is to reduce biases and inaccuracies in a study. This means that if the same research is carried out by other researchers, pursuing the proposed procedures, will arrive at the similar conclusions and findings (Yin, 1994).

Neuman (2000) suggested the three following aspects of reliability: stability, internal consistency and equivalence when addressed the research will deliver the same or similar results.

- Stability reliability, also called test-retest reliability, evaluates how consistent the measurements remain across time. It addresses the issue that the research delivers the same results when applied in a different time period. The researchers proceed by the correlation assessment between the indicator's scores tested at time 1 and retested at time 2. This approach should be taken under the assumption that the time period is long enough that the first test does not influence the second test. However, the major difficulty with this approach is the definition of time interval between the tests.
- Internal consistency is reliability across subparts of studied phenomenon or groups of cases. This approach involves the stability of results when the study is applied to multiple cases. An indicator is internally consistent or homogenous across cases if there are no contradictions in results achieved when applied to different cases.
- Equivalence reliability refers to the level of similarity between options of measuring instruments. When the researchers conduct the study by means of a number of different instruments; equivalence reliability ensures that the measure lead to similar results across multiple instruments.

To achieve and preserve reliability, Brownell (1995) and Yin (1994) have recommended that a case study protocol and database should be constructed; however no common instructions have been delivered. The main objective of the case study protocol, a document describing all the activities during the case study, is to make the methodology possible to replicate in other studies. This provides an overview of research project, questions and phases of the study for different researchers to follow (Brownell 1995). In this research, data requirement, analysis, collection and data sources are set for further recollection and reanalysis.

On the other hand, the implementation and usefulness of the study also compels that the methodology should be academically valid. The latter refers to the strategies aimed to enhance the credibility of the study findings and interpretations leading to the generalisation of the study outputs. Neuman (2003) suggested the following types of validity:

- Internal validity, compulsory only for explanatory or causal studies, tries to study the causal relationships between variables to identify any inferences (Yin, 1994). The specific methods suggested to achieve internal validity are "explanation-building, pattern matching and time series analysis" (Yin 1994). Since this study is mostly concerned with an exploratory approach, internal validity was not applied.
- External validity is concerned to which extent the study outputs can be generalised or be applied to other situations (Yin, 1994). With regard to this research, the findings can be used in some broader situations, which indicate the generality of the research outputs.
- Statistical validity is concerned with the satisfaction of statistical procedure and its assumptions which have been chosen for the study.

5.4 DATA COLLECTION AND ANALYSIS

5.4.1 DATA COLLECTION

Data for case studies may be grouped into two classes: qualitative, in the form of words, or quantitative in the form of numbers (Neuman, 2003). Yin (1994) presented a quite exhaustive list for data sources that comprises archival records, interviews, direct observations and documents. In addition, he provides an analysis of advantages and limitations for each source with regard to different settings of use. This research focuses on quantitative approach to study an event within its real-life environment by collecting evidence (Yin, 1994 and Robson, 1993). Archival records, documentation, direct observation and interview will be therefore quantitative data collection methods used in this research. Accordingly, this research uses secondary data collection methods (organisation documents, maintenance manuals and reports, spare part supplier documents, etc.).

Stake (1995) and Yin (1994) claimed that data sources should be multiple to ensure the reliability of the study. They considered the following list as exhaustive primary sources of evidence. Besides, they specified that not all sources are required in every case study and the use of each source relies heavily on researcher skills and research questions. The data sources categorised by Yin (1994) are:

- documentation,
- archival records,
- direct observation,
- participant observation,
- interviews, and
- physical artifacts.

Table (5.2): Research data sources (Source: Yin, 1994)

Data Sources	**strengths**	**Limitations**
Documentation	stable - repeated review unobtrusive - exist prior to case study exact - names etc. broad coverage - extended time span	retrievability - difficult biased selectivity reporting bias - reflects author bias access - may be blocked
Archival Records	Same as above precise and quantitative	Same as above privacy might inhibit access
Interviews	targeted - focuses on case study topic insightful - provides perceived causal inferences	bias due to poor questions response bias incomplete recollection reflexivity - interviewee expresses what interviewer wants to hear
Direct Observation	reality - covers events in real time contextual - covers event context	time-consuming selectivity - might miss facts reflexivity - observer's presence might cause change cost - observers need time
Participant Observation	Same as above insightful into interpersonal behaviour	Same as above bias due to investigator's actions
Physical Artifacts	insightful into cultural features insightful into technical operations	selectivity availability

No single source has a complete advantage over the others; rather, they might be complementary and could be used in tandem. Thus a case study should use as many sources as are relevant to the study. Table 1 indicates the strengths and weaknesses of each type:

Since this study is conducting an integrated logistics support ILS analysis requires a broad quantity of information and a large amount of this information is available neither in adequate format nor in organisation documents. In general, ILS models deal with the following aspects: a description of a technical system, a modelling of the deterioration and its effect on system operational output, a definition of the available information about the system, a designation of the objective function and the optimisation methods which determine the best trade-off. The data inherent to these ILS aspects consist mostly of failure frequencies, repair time, costs, maintenance capabilities and procedures, spare procurement time, installed repair shops and how ease these shops are interconnected. Beyond these aspects, this study explores also the effect of the operating environment on the research questions through direct observation, questionnaires and the examination of reports and documents. Maintenance data which may be used for integrated logistics support are generally gathered from the following sources:

- Engineering drawings;
- Product data for design and manufacturing;
- Technical specifications and standards;
- Technical publications and handbooks;
- Training materials for maintainers;
- Spare parts descriptions;
- Maintenance plans;
- Maintenance reports;
- Maintenance crew interviews etc.

5.4.2 DATA REQUIREMENTS

The validation of any model outputs dependent mainly upon its modelling tools and the quality of the input data. It is necessary, therefore, that the accuracy of input data is established. In setting up data requirements, the methodology was to ascertain a trade-off between a realistic level of rigor and standardisation, flexible recording database that could be adapted to any specific use and scientific technique requirements used as modelling tools. A thorough analysis of the integrated logistics support ILS techniques has shown that the ILS data requirements could be classified as follows:

- The system level data: a hierarchical system structure should containing all the components and sub-components that are replaceable or to be repaired at the all system breakdown levels. The predicted or observed failure, repair and supply characteristics of these components are necessary. Additionally, a set of other core data should be defined and it may contain general information about the system as capacity, physical dimensions and weight. This information is vital for logistics considerations.
- The operational data: this category may encompass event data (detailed information about the outages or maintenance activities that occur), counter data (cumulative functioning hours since the beginning of operation), environmental data (information about environmental conditions observed at the site), and the required level of availability of the system.
- The support data : may include stock positions and their costs, procurement mean time for each components and are also required, as is deployment a
- The repair facility data: details of the repair shops (their positions, characteristics, and interactions).
- The economic data: the economic data required include the discount rate, inflation rate, direct and common costs and the analysis period (or the life cycle).

5.4.3 DATA ANALYSIS

According to (Yin, 1994 and Miles et al., 1994), the basic purpose of data analysis is to make data readily amenable to mechanical manipulation, analysis, and data reduction. They divided data analysis stage into these categories: examining, categorising, tabulating, or otherwise recombining the evidence to fulfil the study objectives.

An essential part of this study the modelling of required spare parts based on equipment reliability, availability, maintainability and supportability RAMS and effects of the operating environment on equipment operation itself. Support and maintenance actions will only be efficient if they tackle all issues of failure, repair and supply of equipment components. Maintenance decisions based only failure rate excluding repair and support structure and data, are therefore inappropriate for most maintenance actions. Analysing maintenance data without knowing the spare part supply mechanisms can lead to unsuitable results. This is often aggravated by an inadequate system-breakdown or repair structuring which is used in maintenance reporting. From integrated logistics support, basic types of maintenance data are associated with the following classes:

- Exploitation and maintenance requirements;
- Reliability and maintainability characteristics;
- Failure mode, effects and criticality analysis;
- Human resource requirements;
- Support equipment data;
- Infrastructure description; etc.

Essentially only analytical data analysis will be used for the study. Descriptive tables will be mostly employed to study and to transform raw data into a form that would make them ready for further use. From these tables, means and standard deviations will the major useful statistics to be used of different parameters required by the optimisation model. The first step in this data analysis implies the categorising of the data. This involved the breaking down both of studied system on its elementary components and repair network on its basic repair shops. Then, all required data will be coded according to system and repair network breakdown. The level at which system or repair network will be split depends on maintenance and support features and optimisation model dimension. Subsequently, patterns and links within and between these categories will be identified. Next for the purpose of validity, the model was tested for different level of categorisation. Finally, the number spare parts will be estimated in a planning horizon. The following figure summarizes the selected method from the spectre of research modules.

Summary of Research Modules (Yin, 1994)

research use	research objective	research approach		research strategy	data sources	data analysis	Reliability	Validity
Basic	Exploration	Quantitative	Inductive	Experiment	Documentation	Analytical	Stability	Internal validity
Applied	Explanation	Qualitative	Deductive	Survey	Interviews	Logical	Equivalence	External validity
	Description		Adductive	Archival analysis	Direct observation		Representative	Statistical validity
				History	Participant observation			
				Case study	archival records			
					Physical artifacts			

Selected Research Modules

research use	research objective	research approach		research strategy	data sources	data analysis	Reliability	Validity
Applied	Exploration	Quantitative	Adductive	Experiment	Documentation	Analytical	Stability	Internal validity
	Description			Case study	Direct observation		Equivalence	External validity
					Archival records		Representative	Statistical validity

Fig. (5.2): Research methodology modules

5.5 RESEARCH FRAMWORK

5.5.1 BACKGROUND

This section describes the research framework for the level of repair analysis and the spare parts inventory that will contribute significantly towards a cost-effective use of physical systems. Practically, the framework is intended to enhance the efficiency of decisions on how to support maintenance tasks for petroleum systems. This will lead to an optimisation of maintenance costs and, therefore, a minimisation of system WLC. Since maintenance and support decisions are taken at different levels: organisational, tactical and strategic levels; the framework is developed based on such hierarchy.

Lambert (2008) asserts that there is a lack of frameworks for ILS development to address some of the issues associated with the operation of complex systems. He argues that ILS knowledge is available only through military documentations which are regards as equivalent to academic literature. Besides, ILS contribution in asset management is regarded as a competitive edge by various companies and as a result all related ILS information fall under confidentiality considerations. In the literature, the framework proposed by Cavalieri et al. (2008) represents the only research work devoted only to inventory control; the other ILS elements are considered available in sufficient quantities. The framework developed in this research study enlarges the existing framework to include effect of repair facility on spare parts control.

Companies in industries like aviation, maritime, petroleum, power exploit and maintain their own physical assets. Within these organisations, a Maintenance Function (MF) is in charge for maintaining the physical assets. In addition, supply of resources, such as technicians, equipment and spare parts is the responsibility of the Maintenance Support Function (MSF). In this environment, MF and MSF work closely to ensure the best value of installed capital assets (figure 5.3). More precisely, MSF's objective is to support MF for the optimal trade-off between system availability, support resources and operational budget.

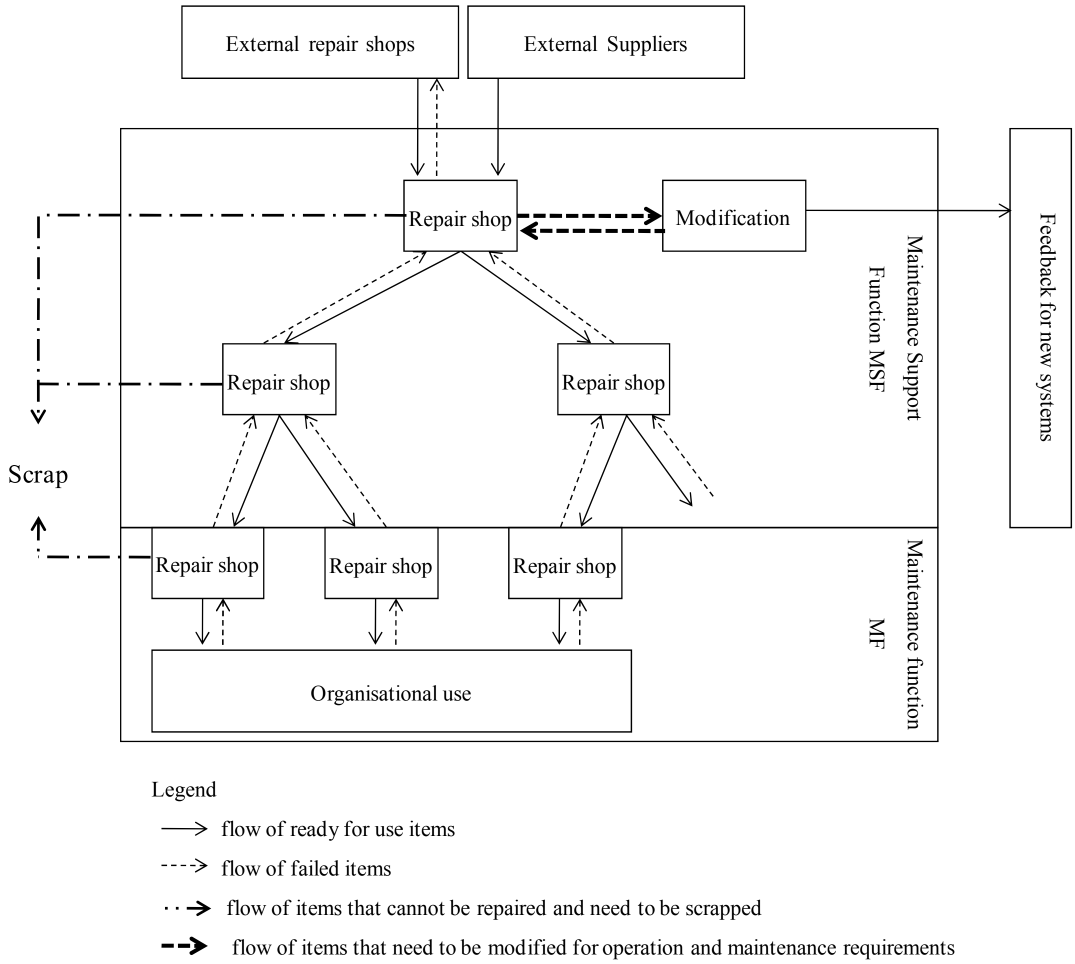

Fig. (5.3): relationship between maintenance function and its support function

The MSF considered in this study supports a set of a number of high-value petroleum assets. Since petroleum companies use sufficiently large range of assets including pumps, turbines, drilling rigs, oil & gas treatment plant, etc., the demand for maintenance tasks are reasonably constant. Consequently, MSF tries to guarantee a prompt response to maintenance work orders by considering maintenance tasks to be conducted and preparing support resources needed to carry out the maintenance. Figure 5.4 highlights a support planning framework for maintenance of installed systems. We notice that the focus of this study (repair capacity planning and spare parts planning) is part of this maintenance and support framework.

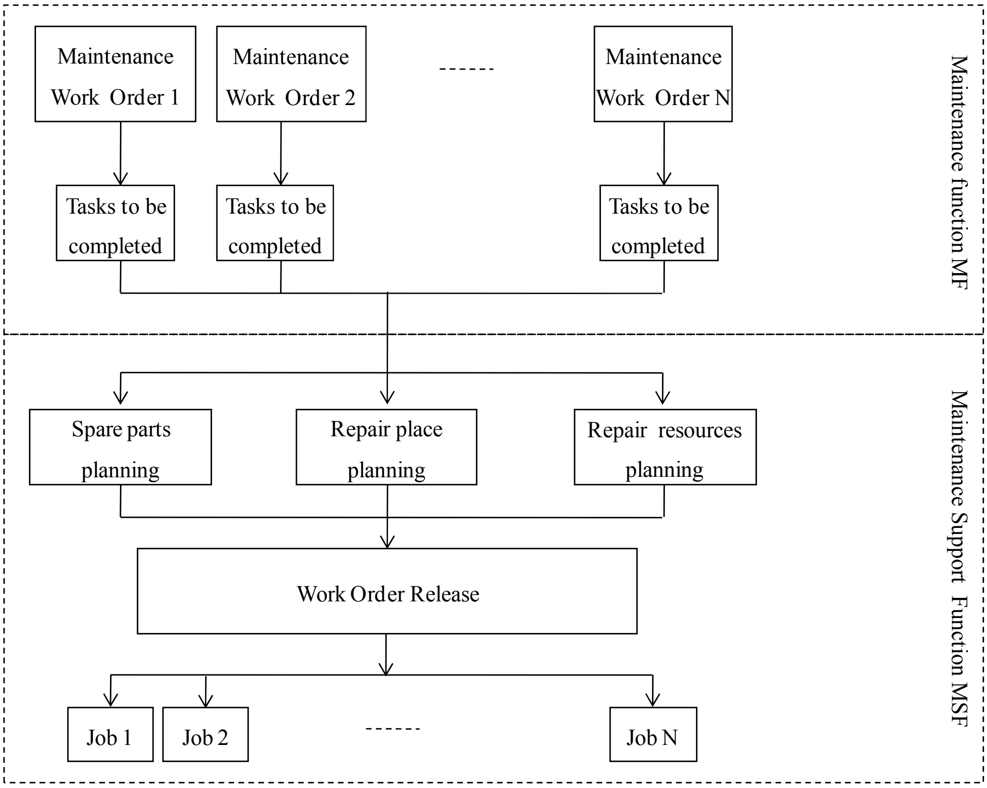

Fig. (5.4): Support planning model

This framework works as follow:

- Work orders are generated from the failed items. These orders come from either installed systems or different repair shops.
- Work orders are releases from MSF as soon as all needed maintenance resources and spare parts are available. The unreleased work orders should wait in queue until the required resources are available.

In practice, Key Performance Indicators (KPI) and the measurement of MF and MSF efficiency are based on the average number of uncompleted work orders. At SONATRACH, national oil company, the number of work orders in repair process represents the average of systems non-functional. Hence the MF and MSF optimise their activities by minimising the number of uncompleted work orders. Even though this work order based KPI is related to system availability, it suffers from two major drawbacks. First, spare parts may keep the system operational while some work orders have been issued from this system. Second, there is no scientific approach that underpins the relationship between maintenance work orders and system functionality.

5.5.2 MAINTENANCE SUPPORT FRAMEWORK

A generic support framework was constructed that explains the integrated logistics support (ILS) contribution for a maintenance optimisation of a system over its whole life-cycle. The needs for such a framework derived from the previous chapters were mainly concerned with a model to maximise the business value of installed systems, and to make sure that both the maintenance and its support functions are included. The two distinctive major ILS elements, namely the spare part inventory management and the level of repair analysis LORA, are employed to optimise maintenance support function and maintenance function respectively. The main emphasis of the model is that LORA and spare part management are the techniques where organisations can make a significant maintenance cost reduction of a set installed systems.

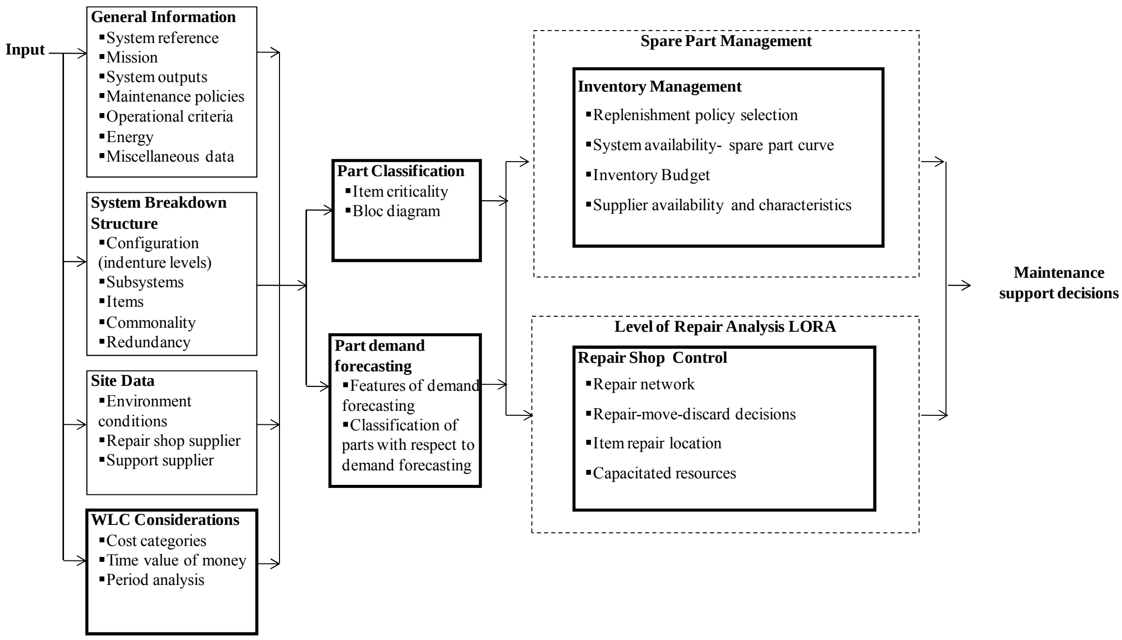

Fig. (5.5): Maintenance support framework

Figure (5.5) shows ILS clustering that underpins MSF's tasks and decisions. Seven new different processes were introduced (bold boxes) in the SOANTRACH model presented by the figure (5.3). As shown, maintenance tasks should be tempered by LORA and spare part management optimisation before the final maintenance decision is made. Another feature of this framework is that it includes part classification process and demand forecasting process regarded as a prerequisite for ILS element optimisation. This procedure is in line with the basic nature of ILS as a technique for information and data collection to support various asset management functions. The main objectives of the introduced models are:

- Part classification is concerned with the component priority decision. Components that are not critical to system functionality their spare parts may be never used during system whole life cycle. Adding this type of parts to the database and spending time on data collection result in unnecessary costs. On the other hand, components that are highly critical to system functionality are usually provides through contracts signed with potential suppliers. In case when suppliers are no longer available, parts may be custom made and the supply lead time is higher due to data gathering and negotiation actions. Example of this sort of parts is turbine blades.
- Demand forecasting concerns with maintenance order fulfilment. It is common that demand predictability of the spare parts is based on part failure rates, operating conditions and maintenance plan (preventive or corrective). Consequently, part demand for spare parts is either planned or unplanned. The overstocking of components that are quite cheap and have a small request for planned or unplanned demand is generally low, and therefore, spending time on demand forecasting is not motivating from a cost perspective. The selection of parts for demand forecasting will be based on the following criteria: (1) the spare part cost and (2) the part criticality.
- The inventory management model is concerned with the stocking decision. This decision is based on the availability of installed systems, operating budget and repair network configuration. Since MSF is in charge of inventory control at all stocking points, there is a mix of spare part storing between central and local bases in order to reduce support costs with respect to system availability. Optimising inventory cost to satisfy system availability should contain the following features: (1) multi-echelon repair network, (2) multi-indenture system structure and (3) system service level. This model is with data obtained from part classification, demand forecasting, general information, site environment and WLC models.
- The repair shop control is concerned with the location where an item should be repaired or scrapped. The outcome of this model is based on the Level-Of-Repair-Analysis (LORA) to select a repair source to install along with item repair decision. The latter entails firstly the case whether an item should be

considered repairable or discardable or and secondly the case where it should be scrapped or repaired. The objective is to attain the lowest repair costs over the whole life of the system. Those costs, delivered by WLC model, include fixed costs and costs that vary with repair work order.

The above sections explain structure and function of the framework, without giving a deep detail on the process. The individual model will be covered comprehensively in the coming chapters.

5.5.3 MAINTENANCE DATA COLLECTION & ANALYSIS

The approach followed in this research needs gathering both qualitative and quantitative data from a studied environment in such a way that can be used with real data to provide optimal maintenance decisions on a real problem. To achieve cost-effective maintenance for petroleum equipment, quantitative methods are the main objective of this research. The main approach applied herein is the integrated logistics support which combines the proven method of spare parts management and level of repair analysis, so far applied to gas turbines with quantitative maintenance optimization techniques. Since maintenance models necessitate numerical computations to find out the optimal maintenance strategies, quantitative information is regarded as an essential part of this optimisation work. Quantitative data was obtained from SONATRACH's maintenance record files. It includes the system breakdown structure, system operation sites, the deterioration and the occurrence of failures of a system, and maintenance actions, etc. A set of gas turbines has been selected to assess the maintenance supportability characteristics of turbines installed in different operating sites. This affects the time of maintenance response to failure, cost of repair actions and the amount of repair resources to be installed not very far from operating sites. All of these constraints are typical issues to be optimised by the framework.

Besides, information concerning maintenance supportability has been also collected through consultations and discussions with SONATRACH's asset managers. This information concerned decision related to spare parts ordering, suppliers selection, and the various kinds of support costs, such as spare pare holding costs, transportation costs, etc. In addition to this, data about the records of replacement schedules and inspections have been also obtained from SONATRACH's archives. Discussions on issues such as replacement and repair performance have been held with experts from the company.

Another important source of maintenance and reliability data that has been used is system manufacturer's guide books and international maintenance and reliability databases such as OREDA. Statistical data analysis for the selected system has been carried out based on data above mentioned resources. In addition, there have been interviews with SONATRACH experts who have professional experience with wind turbine operations and maintenance for the identification of the most critical items through component classification with respect to failure frequency and downtime per failure.

5.6 RESEARCH PROCESS

This research will be completed in three phases as follows (figure 5.6):

5.6.1 PHASE 1

This phase, including chapters 2 to 5, constitutes of the introduction, the theoretical review and the research methodology description. The theoretical review covers topics related to integrated logistics support, level of repair analysis LORA and spare part inventory control. The first chapter provides the background, problem statement, aim and hypothesis of the research. Chapter 2 is a critical review of the integrated logistics supports ILS concept to confirm the problem statement and hypothesis. Chapter 3 is devoted to the analysis of LORA techniques. In chapter 4, spare part inventory control techniques required to achieve an efficient implementation of ILS is critically reviewed. In these chapters the need for a research questions to be answered is investigated, consequently providing justification for the research methodology, which is provided in Chapter 5.

5.6.2 PHASE 2

The second part, including chapters 6 to 8, reports the development of the empirical studies. In chapter 6, a generic optimisation model for LORA analysis is designed. This model has been carried out on real-life data to investigate in-depth the requirements of effective LORA decision-making. Following the knowledge gained on the LORA technique, an understanding of spare part inventory control is the next prerequisite for the ILS model. In chapter 7, the spare part optimisation is discussed. These two techniques have been presented by earlier researchers and generally have been applied separately. In chapter 8, a novel extended application is developed to facilitate the integration of the previous two techniques into one framework for effective maintenance strategies within for petroleum industry.

5.6.3 PHASE 3

The third part includes chapters 9 and 10. Chapter 9 presents the testing and validation of the developed framework. Finally, the research work is summarized, conclusions are drawn and directions for further research work are introduced in chapter 10.

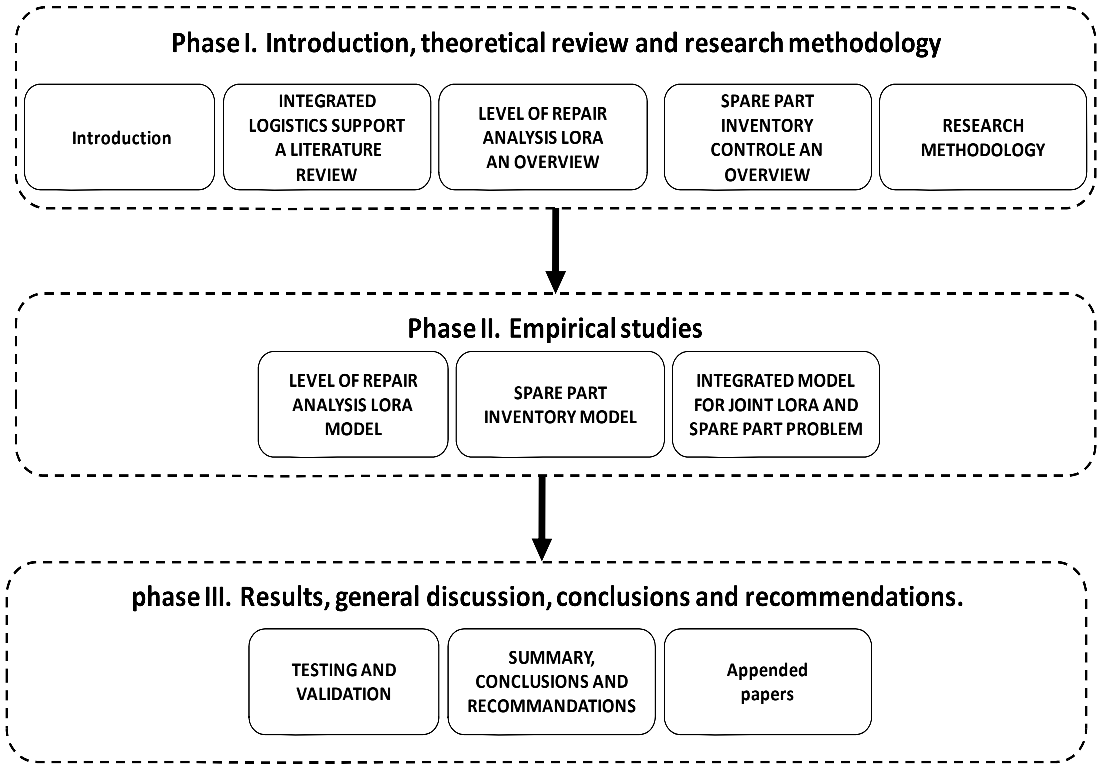

Fig. (5.6): Research process

5.7 SUMMARY

The main purpose of this chapter has been on the research design, selection and motive of research strategy to be used in this study. Experiment has been selected for this study and it is embedded within the case study focusing on research questions. The criteria that underpin this selection are partly due to the aim of the study and partly due to the theoretical techniques used. In addition, plan was given to the reliability and validity consideration, to give credibility to the contribution of the study. Interviews, documents, petroleum equipment supplier data and company reports were set as the main sources for data collection, from Algerian petroleum company SONATRACH. The precise population of this study has been selected from Gas Turbine System.

CHAPTER 6 LEVEL OF REPAIR ANALYSIS (LORA) MODEL

6.1 INTRODUCTION

In chapters 2 and 3, maintenance support policies used to petroleum assets are insufficient to meet the industry expectations have explained. Chapter 2 emphasized the need to include Integrated Logistics Support ILS when setting maintenance policies for installed physical assets. In chapter 3, a hybrid technique encompasses Level of Repair Analysis LORA and Whole Life Costing approaches were developed to define the optimum repair decisions.

In this chapter, a case study is carried out to demonstrate the industrial application of the LORA approach. The LORA analysis identifies suitable maintenance decisions and their locations in repair network. This research focuses on spare parts management in companies in which installed systems are complex and have to perform at high levels of availability and reliability. Examples include military sector, petroleum industry, construction industry and nuclear power plants. The Algerian National Oil Company (SONATRACH) is a typical example of companies equipped with very complex physical systems. The proposed models will be tested on the maintenance of gas turbines which share the same repair structure. Investing in repair locations is vital when performing LORA for these assets, since they operate over a large area, including remote sites in the Algerian desert. The LORA trade-off analysis seeks to minimise part transportation costs by installing repair shops nearer to the operation sites or to minimise maintenance costs by installing central repair shops, usually near to urban and industrial areas.

The remainder of this chapter is organised as follows. The LORA model that is developed to solve problem of the repair location selection is formulated in Section 6.2. In Section 6.3, a case study to illustrate the model is presented. The choice of genetic algorithms as optimisation technique is given in Section 6.4. The computational experiments and results are reported in Section 6.5. A summary of chapter findings is presented in Section 6.

6.2 THE LORA MODEL

Consider an organisation possessing K systems working in different zones or areas. Any system includes N items which have each three repair states: under repair (r), discard (d) or moving to another repair shop (m). Denote M the number of repair levels. The entire system has 3*M*N different repair states, which may be extremely high for thousands item system. The repair performance is measured by the whole costs to accomplish repair tasks, which are variable costs changing with the repair demand and the fixed costs representing the installed support resources at the repair shops. Therefore, the repair decision problem is a combinatorial optimisation problem to identify the number of repair shops (central depot, intermediate repair shops and local repair shops) and assign component inspection and reparations to these in order to minimise the whole life cost.

6.2.1 ASSUMPTIONS

The basic assumptions when conducting LORA exercise are:

- The repair network comprises a number repair shops structured into hierarchical levels called multi-echelon structure. At the top, there is a central depot where the most support and test equipment is installed. For economic concerns, the upper levels contain more support and test equipment than lower ones.
- The reparation of the installed systems (indenture level 0) does not consist of moving them from their place, but always consists of isolation and repair of the failed LRUs.
- Each time a repair, discard or move decision is taken at a certain echelon level, variable costs and annual fixed costs are incurred.
- When a failed item cannot be repaired at a certain echelon level j, it will be sent to echelon level j + 1.
- When an LRU is repaired at echelon level j, its failed SRU will be repaired at echelon level $k \geq j$.
- When repair decision is made for a certain item at a certain echelon level, the repair is considered successful at 100%.
- There are three possible decisions at each echelon and for each item:

- Discard: item i is scrapped and a ready-for-use item is acquired.
- Repair: item i is repaired by replacing its failed child (or children) by ready-for-use one (ones).
- Move: item i is moved to higher repair level where repair-discard-move decision should be taken.

6.2.2 NOTATION

The following notations are adopted herein:

m the number of the echelons in the repair network.

n the total number of components for the system under consideration.

r repair options: repair, discard or move.

λ_i Total number of maintenance tasks required in the whole life time of component i.

$FC_{r,e,i}$ fixed cost related to repair option 'r ' at echelon 'e' and for component 'i'.

$VC_{r,e,i}$ variable cost related to repair option 'r' at echelon 'e' and for component 'i'.

X vector containing three binary values (6.1) which should be defined for any item and at any echelon.

Component i is the parent of the component j or component j is the child of the component i.

$$\begin{array}{c} repair discard move \\ X = [1\ or\ 0 \quad 1\ or\ 0 \quad 1\ or\ 0] \end{array} \tag{6.1}$$

6.2.3 LORA PROBLEM FORMULATION

The binary LORA problem is formulated based on the notation mentioned above as follows:

$$X_{r,e,i} = \begin{cases} 1 & \text{if repair option r at echelon e is selected for part i} \\ 0 & \text{otherwise} \end{cases} \tag{6.2}$$

$$\sum_{i=1}^{n}\sum_{r=1}^{3}\sum_{e=1}^{m}(VC_{r,e,i} * \lambda_{\mathrm{i}} + \mathrm{FC}_{r,e,i}) * X_{r,e,i} \tag{6.3}$$

Subject to

$$X_{r,e,i} = 1\, forallitems \tag{6.4}$$

$$X_{move,e,i} = X_{r,e+1,i} = 1 \tag{6.5}$$

$$\begin{cases} X_{r,e,i} = X_{r,e,j} \\ when\ i\ is\ parent\ of\ j\ and\ r = discard\ or\ move \end{cases} \tag{6.6}$$

The constraint in Equation 6.4 means that one repair decision (repair, discard or move) should be taken for each item at nay repair echelon and the constraint in Equation 6.6 define the relationship between parent and children repair decisions.

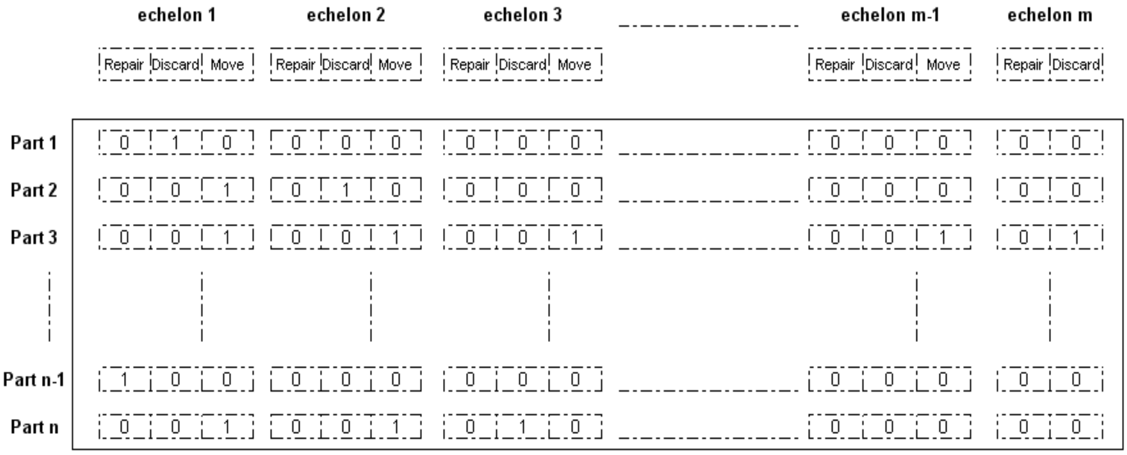

Fig. (6.1): Sample of repair decision

In considering this mathematical formulation, the significant practical issue is related to designing a variety of different repair alternatives for each item along with required maintenance support resources. That is, each item may have 3 repair states at any echelon and 3*m repair states all over the repair network to be considered. This combinatorial situation of choosing repair decision, as illustrated by figure 6.1, makes the LORA optimisation model difficult to resolve, which is called a NP-hard model.

6.3 A CASE STUDY

6.3.1 DESCRIPTION

SONATRACH, the Algerian National Oil & Gas Company, owns and operates oil & gas fields, refineries, LNG plants and oil & gas transmission network in Algeria. This network ensures the flow of hydrocarbons (crude oil, natural gas, LPG and condensate) from the Algerian desert to the exporting ports in the north and to the south of Europe. Algeria's Petroleum Transmission System consists of 16 200 km of pipelines of different designation and capacity, and 79 pumping and compressor stations equipped with over 290 main machines with a total capacity of over 02 millions horse-power. The efficiency of this transmission system relies heavily on the availability of the installed gas turbines. This equipment converts the thermal energy produced by fuel combustion into mechanical energy to revolve the compressor's shaft.

Fig. (6.2): Gas turbine

A real gas turbine system is considered in this research. The selection of this class of petroleum equipment is intentional for a number of reasons; first, this equipment is installed in a spread area along with pipeline routes; secondly, its repair is undertaken in hierarchy structure which consists of local and intermediate bases. These two reasons fit perfectly the process of LORA and spare part models. Figure (6.3) represents a material breakdown structure of gas turbine used in boosting station like PGT10, PGT16, PGT25 and ALSTOM. These systems, which comprise various repairable and consumable parts, play a key role in the operation of the Transmission System. For large companies, such as a petroleum company, enhancing operation performances of such asset at reduced costs related to repair and maintenance tasks are one of the major of management concerns. In relation to this, the case studies conducted in this research mostly concern maintenance supply with spare parts of gas turbines, such as blades, shaft, gears, compressor and some other parts. In response to these concerns, the case studies were carried out for identifying the optimal number of spare parts with regard to the operating requirement.

Based on ILS standard and guidelines, the first step of LORA and spare part analysis is to generate or adopt a system breakdown structure that categorises all relevant components in hierarchical format. In a typical LORA analysis, a system is defined as a collection of components. These components are usually the items, parts, equipment or subsystems of the system. The proposed system breakdown structure is divided into three levels (Figure 6.1). This engine modules are maintained based on fixed operating time (8 000 hours, 16 000 hours and 32 000 hours), on corrective reactions and on condition using. As an engine undergoes maintenance tasks at the repair shop, different subsystems and components are replaced by new or restored ones. The failed items are scrapped, or repaired then tested at three local repair bases or at three intermediate bases.

6.3.2 DATA COLLECTION

Three main sources of ILS data should be identified: manufacturers' and suppliers' data, organisation data, historical data and predictive model data. In LORA analysis, this data will be split furthermore into two principal categories: data related to the system itself and data related to the repair shops. The first category includes the following information: turbine ID, list of material, item procurement cost, dates of maintenance events, repair interval, downtime and maintenance comments. The above gas turbines are similar in type, structure and functionality and each of them consists of the following subsystems, namely, turbine, compressor, combustion system, air inlet system, start-up system and turnion support.

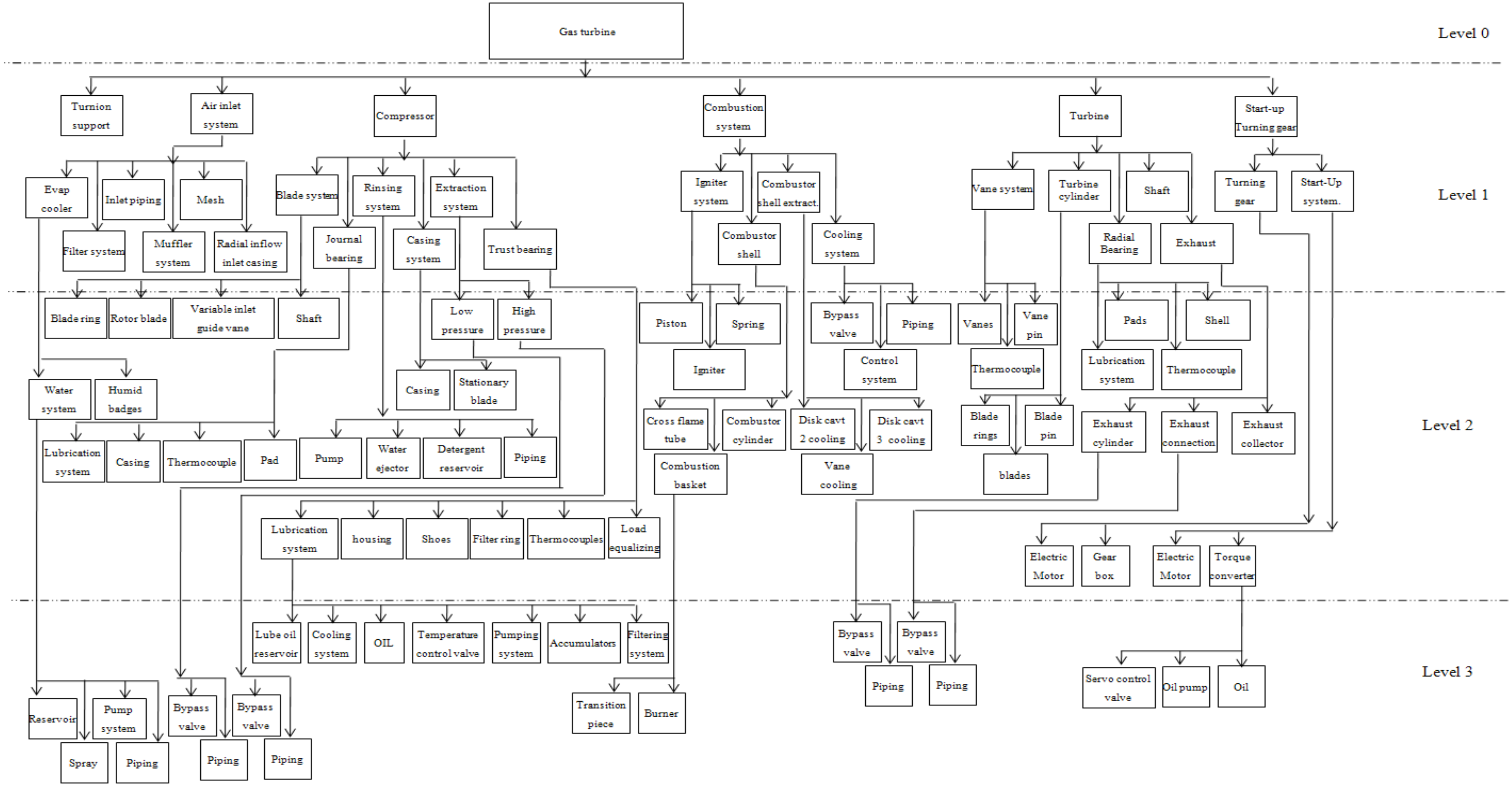

Fig. (6.3): Gas turbine breakdown structure

System related data is collected through the maintenance work orders and the maintenance reporting system at the company. In these archives, the available information is; the work order starting date, the work order finishing date, system ID, failed subsystem or subsystems, replaced item or items, type of system downtime (total, partial or minor downtime) and the reasons for failures. Unfortunately, all these data sources do not contain cost information such as: repair cost, spare part cost, etc.

The relevant data for LORA analysis consists of the following three characteristics: (a) the number of stops; (b) failed item (s) and (c) stop time. The intent behind the LORA analysis is to check whether the repair actions are optimally designed or not. The table 6.1 summarises the LORA data of the different turbine subsystems. The last two columns give the mean time between failure of the selected components and their repair demand. Due to confidentiality reasons, it has not been allowed to present the real data of the case study used to evaluate LORA model. Consequently, all cost values in the table 6.1 are presented in modified monetary unit symbolised by MU.

The second LORA required data is the costs for repair actions. For gas turbine example, these costs are repair facility cost, support and test equipment cost and labour cost. In order to evaluate the economic consequences of repair actions it is essential to distinguish between fixed costs and variable costs. The fixed costs class is characterised by installed capacity which does not increase with the failure rate up to a certain limit. These costs are normally defined for each echelon of maintenance and they may include the following subclasses:

- Repair shops building
- Support and test equipment
- Manpower cost
- Documentation

Another issue arises when considering the fixed costs is that all above subclasses is devoted to a set of operational systems such: turbines, compressors, pumps, etc. In order to allocate costs to each system, repair capacity is firstly split into direct and indirect costs then indirect cost are allocated to system by means of repair demands. Besides, variable costs are continuous functions which vary with the failure rate such as: spare part costs and labour costs. Following WLC mathematical expression, repair cost for the

Table (6.1): Lora model data

Nº	items	FIXED COSTS									VARIABLE COSTS								Repair demand	
		ECHELON 1			ECHELON 2			ECHELON 3			ECHELON 1			ECHELON 2			ECHELON 3		MTBF	Annual repair demand
		r	d	m	r	d	m	r	d		r	d	m	r	d	m	r	d	days	failure/annum
1	**Turnion support**	**130**	**200**	**60**	**174**	**129**	**57**	**147**	**123**		**839**	**1284**	**385**	**1117**	**828**	**366**	**944**	**789**	**3318**	**0,110**
2	**Air inlet**	**280**	**387**	**66**	**314**	**319**	**63**	**289**	**248**		**1773**	**2444**	**416**	**1983**	**2015**	**397**	**1825**	**1566**	**2225**	**0,164**
3	Evap cooler	314	511	62	293	300	55	259	241		1891	3079	373	1764	1806	331	1559	1451	1241	0,294
4	Water system	340	369	67	317	325	59	280	261		2097	2276	413	1955	2005	364	1727	1610	2433	0,150
5	Humid badges	320	347	63	298	306	56	264	245		2051	2224	403	1910	1962	359	1692	1570	3041	0,120
6	Inlet piping	462	612	67	317	350	64	268	335		2886	3823	418	1980	2187	399	1674	2093	2085	0,175
7	Mesh	350	520	66	298	325	61	294	212		2182	3244	411	1858	2026	380	1833	1321	2683	0,136
8	Filter system	298	493	72	258	291	71	252	227		1846	3057	446	1598	1803	439	1561	1406	2198	0,166
9	Mufflersystem	298	465	63	239	291	60	170	259		1886	2943	398	1513	1842	379	1076	1639	2185	0,167
10	Radial inflow inlet casing	316	511	78	268	261	75	156	233		1911	3093	471	1620	1578	453	943	1409	2552	0,143
11	**Compressor system**	**207**	**433**	**83**	**275**	**396**	**79**	**243**	**250**	0	**1262**	**2632**	**504**	**1672**	**2407**	**480**	**1477**	**1520**	**2588**	**0,141**
12	Blade system	356	395	58	300	508	52	214	299	0	2163	2400	352	1822	3088	315	1300	1816	2172	0,168
13	Blade ring	382	568	72	325	532	66	321	231	0	2420	3601	456	2059	3373	418	2034	1463	1921	0,190
14	Rotor blade	363	540	68	309	505	63	305	220	0	2340	3481	438	1992	3258	406	1966	1418	2807	0,130
15	Variable inlet guide var	342	553	84	290	423	81	168	252	0	2128	3444	522	1804	2631	504	1045	1568	3318	0,110
16	Shaft	324	525	80	275	402	77	160	239	0	2091	3388	516	1775	2593	497	1032	1542	3318	0,110
17	Rinsing system	235	266	68	231	300	66	202	192	0	1494	1692	432	1469	1908	419	1285	1221	2310	0,158
18	Pump	333	388	82	282	412	79	264	245	0	2010	2344	495	1702	2490	477	1594	1479	3318	0,110
19	Water ejector	345	363	85	292	427	81	270	254	0	2241	2358	552	1897	2778	526	1754	1650	3318	0,110
20	Detergent reservoir	334	540	82	283	414	79	165	246	0	2055	3322	504	1741	2547	486	1015	1513	3318	0,110
21	Piping	340	444	83	288	271	80	268	250	0	2129	2781	519	1804	1699	501	1678	1566	1520	0,240
22	Extraction system	300	256	68	144	352	65	126	182	0	1929	1646	437	926	2266	417	810	1170	2664	0,137
23	Low pressure	370	483	90	313	295	87	291	272	0	2264	2955	550	1915	1807	532	1780	1664	1586	0,230
24	High pressure	376	490	91	318	300	88	296	276	0	2344	3058	567	1983	1870	548	1845	1721	1586	0,230
25	Journal bearing	187	275	64	171	288	62	166	157	0	1173	1726	401	1073	1807	389	1042	985	2664	0,137
26	Lubrication system	337	393	83	286	417	80	267	248	0	2028	2364	499	1721	2509	481	1606	1492	2433	0,150
27	Casing	357	375	87	302	442	83	279	262	0	2254	2367	549	1906	2793	524	1761	1654	1303	0,280
28	Thermocouple	342	558	67	319	490	60	282	263	0	2104	3433	412	1962	3018	369	1735	1618	1351	0,270
29	Pad	364	424	89	309	450	86	288	268	0	2208	2575	540	1875	2730	521	1747	1626	1351	0,270
30	Casing system	284	308	59	248	408	57	140	173	0	1705	1849	354	1489	2449	342	840	1038	2664	0,137
31	Stationary blade	299	699	63	239	438	60	170	259	0	1895	4437	399	1515	2776	380	1077	1642	1351	0,270
32	Casing	351	783	66	299	489	61	295	212	0	2158	4812	405	1838	3006	375	1814	1303	2281	0,160
33	Trust bearing	308	272	44	211	349	42	178	223	0	1980	1748	282	1356	2245	270	1144	1433	2016	0,181
34	Lubrication system	484	960	70	332	549	67	280	350	0	3022	5998	437	2073	3427	418	1748	2185	1921	0,190
35	housing	497	987	72	341	564	68	288	360	0	3188	6336	461	2187	3618	436	1847	2309	1921	0,190
36	Shoes	355	694	86	300	283	83	280	261	0	2306	4515	558	1949	1842	539	1819	1695	1921	0,190
37	Filter ring	383	751	93	324	306	90	301	282	0	2382	4672	578	2015	1903	559	1872	1754	1403	0,260
38	Thermocouples	411	802	99	348	327	96	323	302	0	2641	5161	636	2236	2101	617	2076	1941	1520	0,240
39	Load equalizing	340	825	84	289	421	80	168	251	0	2089	5073	516	1775	2589	491	1032	1542	1921	0,190
40	**Combustion system**	**166**	**242**	**65**	**208**	**225**	**63**	**177**	**194**		**997**	**1454**	**390**	**1249**	**1351**	**378**	**1063**	**1165**	**1834**	**0,199**
41	Igniter system	303	329	63	265	291	60	149	185		1867	2028	388	1633	1793	369	918	1140	2198	0,166
42	Piston	322	520	79	273	399	76	159	237		1988	3214	487	1686	2463	469	982	1463	1921	0,190
43	Igniter	362	538	68	308	504	63	304	219		2348	3492	441	1998	3268	408	1972	1420	1303	0,280
44	Spring	334	540	82	283	414	79	165	246		2157	3487	529	1828	2673	510	1065	1589	2147	0,170
45	Combustor shell extract.	324	352	67	283	311	64	159	197		1968	2138	407	1719	1889	388	966	1196	2401	0,152
46	Disk cavt 2 cooling	377	561	71	321	525	65	316	228		2308	3435	434	1965	3214	398	1935	1396	2147	0,170
47	Disk cavt 3 cooling	338	547	83	287	418	80	167	249		2139	3465	525	1816	2647	506	1056	1575	2147	0,170
48	Vane cooling	335	541	82	284	414	79	165	247		2093	3384	512	1775	2587	493	1031	1543	2027	0,180
49	Combustor shell	346	376	71	302	332	68	170	210		2179	2368	447	1902	2091	428	1070	1322	3348	0,109
50	Combustor cylinder	372	553	70	317	517	64	312	225		2350	3496	442	2003	3270	404	1971	1421	1403	0,260
51	Combustion basket	329	532	81	279	406	78	162	242		2057	3328	506	1744	2541	487	1013	1513	1403	0,260
52	Cross flame	329	532	81	279	408	78	162	242		1975	3196	486	1674	2448	468	972	1452	1351	0,270
53	Cooling system	465	411	67	319	352	64	270	337		2866	2533	413	1966	2169	394	1664	2077	3379	0,108
54	Bypass valve	407	532	98	344	324	95	320	299		2547	3333	613	2153	2028	594	2002	1871	1659	0,220
55	Control system	472	625	68	324	537	65	274	342		2966	3930	427	2036	3373	408	1721	2149	1520	0,240
56	Piping	501	663	72	344	568	69	290	363		3109	4114	446	2135	3528	428	1799	2252	1520	0,240
57	**Turbine**	**176**	**281**	**67**	**206**	**276**	**60**	**186**	**255**		**1139**	**1817**	**433**	**1332**	**1785**	**388**	**1203**	**1649**	**1682**	**0,217**
58	Vane system	318	343	78	270	263	75	157	234		1919	2069	470	1629	1587	452	947	1412	2198	0,166
59	Thermocouple	344	558	85	292	426	81	170	254		2078	3370	513	1764	2572	489	1027	1534	1460	0,250
60	Vanes	320	517	79	271	396	76	158	236		2046	3309	505	1733	2532	486	1010	1509	1921	0,190
61	Vane pin	338	547	83	287	418	80	167	249		2171	3516	533	1843	2688	513	1072	1599	2433	0,150
62	Cylinder Turbine	382	379	72	326	355	66	321	231		2351	2332	443	2006	2185	406	1975	1421	2874	0,127
63	Blade rings	352	523	66	300	490	61	296	213		2229	3315	417	1899	3105	386	1874	1348	2433	0,150
64	Blade pin	339	549	83	288	420	80	167	250		2184	3537	534	1855	2706	515	1076	1611	2433	0,150
65	blades	322	520	79	273	399	76	159	237		2033	3286	498	1724	2518	479	1004	1496	1351	0,270
66	Shaft	345	373	85	293	285	82	170	254		2241	2423	552	1903	1851	532	1104	1650	2239	0,163
67	Radial Bearing	368	365	69	313	342	64	309	223		2283	2264	428	1942	2122	397	1917	1383	2664	0,137
68	Thermocouple	367	546	69	312	511	64	308	222		2204	3279	414	1874	3072	384	1850	1333	1825	0,200
69	Pads	362	538	68	308	504	63	304	219		2251	3348	422	1915	3133	391	1890	1362	1825	0,200
70	Lubrication system	377	559	71	321	525	65	316	228		2271	3370	427	1933	3162	391	1903	1373	1825	0,200
71	Shell	304	474	64	244	445	61	173	264		1924	3000	405	1544	2818	386	1095	1671	1825	0,200
72	Exhaust	332	359	82	282	274	79	164	245		2028	2193	501	1723	1674	482	1002	1496	2664	0,137
73	Exhaust collector	367	546	69	313	511	64	308	222		2299	3420	432	1960	3204	400	1929	1390	1303	0,280
74	Exhaust cylinder	383	568	72	326	532	66	321	232	0	2314	3433	435	1969	3216	398	1939	1401	1303	0,280
75	Exhaust connection	374	556	70	319	522	65	314	227	0	2304	3429	431	1965	3216	400	1935	1398	1460	0,250
76	**Turning gear**	**169**	**254**	**67**	**200**	**226**	**60**	**196**	**201**	0	**1060**	**1593**	**420**	**1254**	**1417**	**376**	**1229**	**1260**	**1891**	**0,193**
77	Turning gear	337	366	66	315	322	59	278	259	0	2124	2307	416	1985	2029	371	1752	1632	2354	0,155
78	Electric Motor	315	513	62	294	451	55	260	242	0	1965	3199	386	1834	2815	343	1622	1509	1659	0,220
79	Gear box	493	652	71	338	559	68	286	357	0	3122	4131	449	2140	3543	430	1811	2260	1921	0,190
80	Start-up system	324	352	64	303	310	56	268	249	0	2091	2272	413	1956	2001	361	1730	1607	2607	0,140
81	Electric Motor	343	558	67	320	490	60	283	263	0	2086	3393	407	1946	2982	364	1721	1599	2433	0,150
82	Torque converter	462	612	67	317	525	64	268	335	0	2799	3708	406	1921	3181	387	1624	2030	2433	0,150

whole life of the turbine, presented by the present value PV, is given by (as described in chapter 3):

$$NPV_{repair} = FC_{repair} + \sum_{k=1}^{N} \frac{\lambda_{repair} * VC_{repair} * (1+d)^k}{(1+i)^k} \tag{6.7}$$

$$NPV_{discard} = FC_{discard} + \sum_{k=1}^{N} \frac{\lambda_{discard} * VC_{discard} * (1+d)^k}{(1+i)^k} \tag{6.8}$$

$$NPV_{move} = FC_{move} + \sum_{k=1}^{N} \frac{\lambda_{move} * VC_{move} * (1+d)^k}{(1+i)^k} \tag{6.9}$$

Where:

λ_{repair}, $\lambda_{discard}$ and λ_{move} denote the annual demand for repair, discard and move respectively.

FC and VC are fixed and variable costs.

i and d are the discount rate and the inflation rate respectively.

Since every system has a predefined useful life based on technological considerations, operation requirements and physical characteristics (FAA Life Cycle Cost Estimating Handbook, 2002), gas turbines usually operate over 25 years. In case of SONATRACH, some gas turbines have been in operation since the 70s; therefore, 30 years will refer to study period in this LORA model. In addition, SONATRACH uses discount rate of 10% and 1.5% as the inflation rate for all financial analysis. Using this information, the cost data for LORA model is evaluated and presented in table 6.1.

6.4 OPTIMISATION TECHNIQUE

The LORA analysis can sometimes be a complex optimisation problem when the system under study encompasses thousands of items. Therefore, a complete examination of all solutions is not reasonable. This type of optimisation problems can be solved within a realistic amount of time only if problem size is relatively small. This has encouraged the use of heuristic algorithms that look for good solutions which may not necessarily the best solution. Under this category of algorithms, the Genetic Algorithms GAs have been proven to be successful optimisation methodology for a variety of applications. They are based on the theory of evolution in solution space. Back (1996) asserts that GAs can find solutions close enough to the best one in a reasonable amount time.

6.4.1 HYBRID GENETIC & TABU SEARCH ALGORITHMS

Either the genetic algorithm GA or the Tabu Search TS are suitable tools for solving such problems. In the literature, however, several researchers have tried to combine these two algorithms to enhance their capabilities in solving combinatorial optimisation (Zdanski & al., 2002 and Hagemana & al., 2003). For instance, a GA speed is low for the huge size population and TS relies strongly on the initial solution. Consequently, GA and TS combination named GATS may overcome these limitations and maintain their advantages.

6.4.1.1 GENETIC ALGORITHMS

Genetic algorithms are stochastic search techniques based on the theory of evolution for finding the global optimum solution. The genetic algorithm developed by Holland to optimise a function F(x), where x is a vector representing individual solutions (Gen & al. 2000). First of all, Genetic algorithms generate not only a single solution but a group of solutions, called a population. This population changes over time, but it always keeps its initial size. The population members are called strings or chromosomes from which a subset called parents is selected according to the best values of F(x). A fitness value in Genetic algorithms is a measure of goodness of a solution to the objective function, i.e., the fitness of an individual is directly related to its objective function value. At any iteration, a fitness value is calculated for each of the current individuals. The selection rule, called a survivability test, exclude from the population the strings which have the worst finesses. Second, new solutions called children (or offspring) are produced by genetic operators: crossover and mutation. Together parents and new children are grouped in a new population which will pass again through survival test. Thus, the population as a whole moves iteratively towards better solutions ideally to the global optimum.

6.4.1.2 CHROMOSOME REPRESENTATION

The first step in implementing a genetic algorithm for a particular problem is to adopt a suitable chromosome representation. The representation scheme developed for LORA analysis is a (n x d) binary matrix, where n is the number of all parts under consideration and d is the number of all the repair decisions throughout the repair network. A value of 1 in this representation implies that a repair, discard or move decision has been attributed to the component i and the repair echelon j. The binary representation of any chromosome or solution is visualised in Figure 6.1. Furthermore, any technical system may be considered as collection of assemblies which are in turn considered as a collection of a set of subassemblies. The number of levels, also referred as indenture levels, in the material breakdown structure of technical system is limited to the deeper detailed information needed for repair tasks and spare-part provision.

For a modelling perspective, the system breakdown structure is represented by a matrix, referred in the literature by commonality matrix (figure 6.4), where the column represents parent items and in the row are child items. We start by assorting parts from the first indenture until the penultimate indenture in the column as parent items. Then, we insert parts from the second indenture to the last one in the commonality matrix row. As shown, child parts 5, 6 and 7 belong to parent part 3 or parent part 3 is constituted of child parts 5, 6 and 7. According to this representation, whenever the parent part 3 is under discard or move decision, the child parts 5, 6 and 7 will have the same decision (constraint Eq. 4).

Parent Parts \ Child parts	1	2	3	4	5	6	7	…	m1
1	0	1	0	0	0	0	0	…	0
2	0	0	1	1	0	0	0	…	0
3	0	0	0	0	1	1	1	…	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮		⋮
n1	0	0	0	0	0	0	0		1

Fig. (6.4): Matrix representation for system structure

6.4.2 GENETIC ALGORITHM OPERATORS

The GATS algorithm uses fitness proportional selection with roulette wheel sampling for crossover operator. At each generation Elitism is applied in this study by replacing the worst solution by the best one with respect to total cost given in Eq. (6.3). After a pair of parents is selected, the crossover operator produces two new children or off springs. The crossover operator is applied on these two parent chromosomes by interchanging the information extracted from them. Since each parent's genetic code has the same structure, we apply the one-point crossover by considering the same crossover point selected at random. The children are generated by combining the left and right parts (figure 6.5);

which is followed by adjusting the offspring repair decisions with respect to the constraint Eq. (6.4).

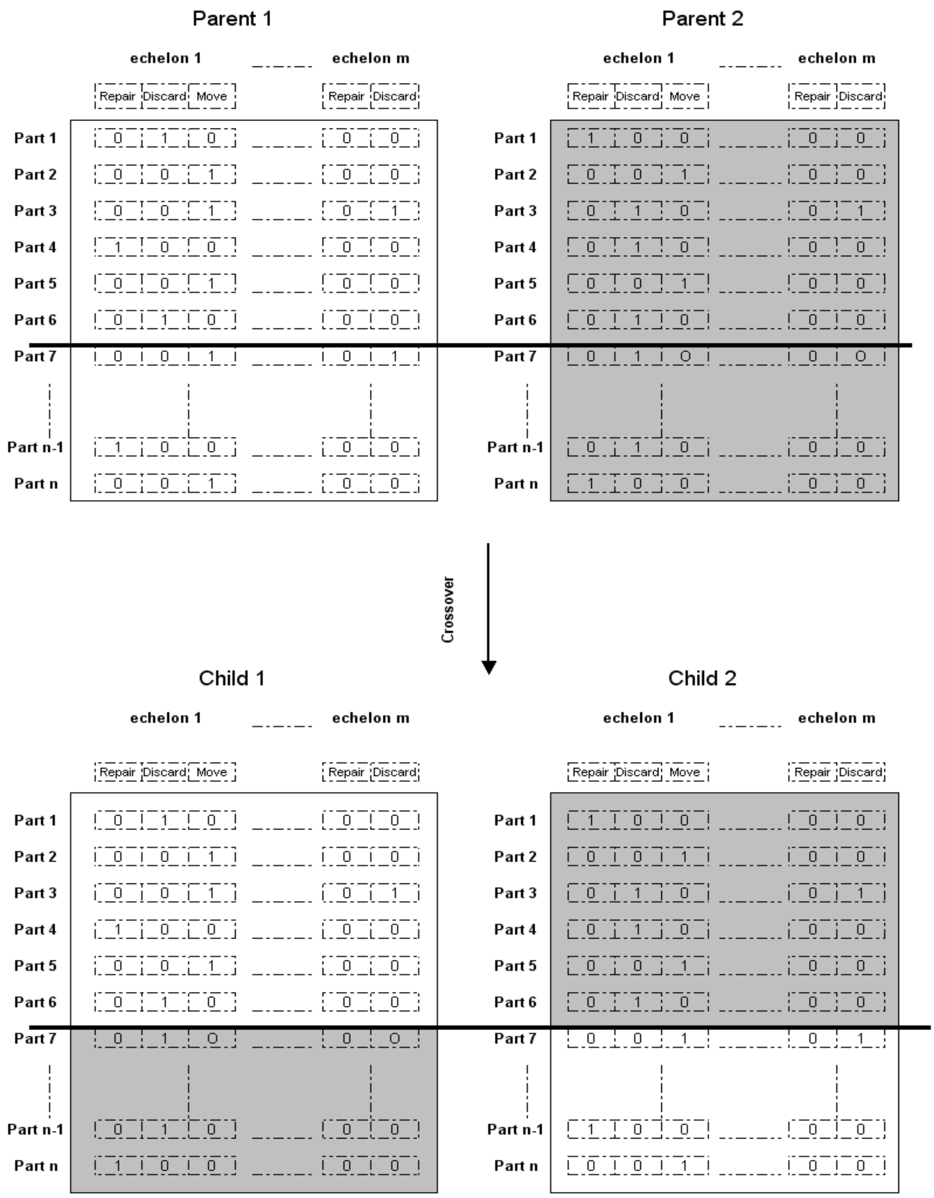

Fig. (6.5): An example use of the crossover operator

On the other hand, mutation is the other important element in genetic algorithms that creates randomly new children. This operator serves as a strategy to prevent solutions from being trapped in local optima. In this work, the mutation operator works by selecting randomly one chromosome outside the best solution list and replacing it by a new chromosome also generated randomly. In addition, we select one of the best solutions and we generate a repair decision for a component selected at random. Again, we adjust the new changes according to the constraint Eq. (4). In our GATS algorithm, these two operators are applied for the individual generated by Genetic Algorithm and improved by TABU search.

6.4.3 TABU SEARCH

TABU Search, concept based on the use of memory, tries to keep track of solution already visited. By leading the optimisation to new areas, TS is able to attain the global optimum instead of local minima. The framework of TS consists of generating some neighbouring solutions from an initial solution (Eswaramurthy & al., 2009). These solutions are evaluated by means of objective function and sorted. The tabu list is updated by the best solution according to its fitness. Afterwards, a new solution is identified and additional neighbouring searches are generated from it. When the best solution remains unchanged after a number of iterations, the optimum is achieved and the best solution will be returned.

The procedure of TS consists of the following steps as depicted in figure (6.6). First, a number of neighbourhood solutions that can be produced from an initial solution are examined. Then, a solution with the best fitness value which is outside of the tabu list is selected from the explored neighbourhood. This way, TABU search tries to assure that the method does not re-examine a solution previously generated. Finally, TS procedure iterates the previous step until no more neighbours are present (all are tabu), or when during a predetermined number of iterations no improvements are found.

6.4.4 GENETIC & TABU SEARCH ALGORITHM

This approach, widely used in the literature, combines the advantages and mitigates the disadvantages of the two algorithms. TABU search relies only on one solution and miss information of a larger set of solutions, however, Genetic Algorithms lead to lower solution quality with increasing problem size (Zdanski & al., 2002). In this study the GATS algorithm starts by generating N initial possible solutions (figure 6.6). A TABU search, as an iterative process, is then used for upgrading these solutions through neighbouring exploration. Afterwards, the flow returns to the Genetic Algorithm which is again an iterative process. By means of the genetic operators new off springs are produced. Then, a TABU list of the best solutions is updated by the new off springs according to the fitness value. The stopping criteria for the GATS algorithm are a predefined number of consecutive iterations attaining the same best solution is reached.

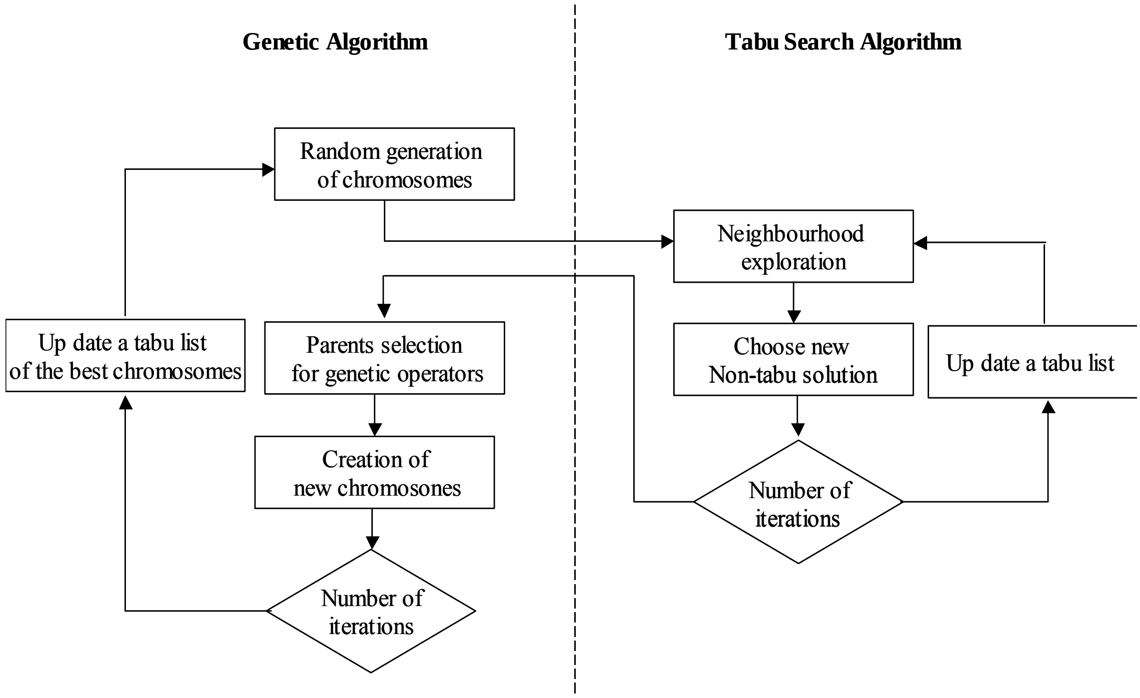

Fig. (6.6): General flowchart of the GATS algorithm

The main steps of the algorithm are shown in figure 6.6 and are described as follows:

- Generate randomly a set of solutions (20 solutions) verifying the equations 2, 3 and 4.
- Refine each solution by the neighbourhood routine with respect to fitness value. A neighbourhood solution is obtained only by modifying the value of one element from the solution under consideration to 1 or 0. Besides, the neighbourhood solutions are not accepted until they verify the constraint equations 2, 3 and 4. Then, a tabu list is updated containing all the fitness values of the solutions that have been explored. After, a new neighbourhood is explored only when its fitness value does not exist in the tabu list.
- Repeat step 2 until there is no improvement of the best fitness value.
- Replace the solution by its best neighbourhood.
- Choose two solutions to produce new chromosomes using genetic operators: parent selection and crossover. These new solution are accepted when they verify the constraint equations 2, 3 and 4.

- Create new chromosomes using genetic operator: mutation.
- Update a tabu list of the best chromosomes.
- Repeat step 1 until there is no improvement of the best chromosome.

The proposed algorithm has been implemented into a computer routine using the MATLAB® programming environment (The MathWorks, 2008).

6.5 COMPUTATIONAL EXPERIMENTS

In this section, we present the results of numerical experiments to test the effectiveness of our LORA model. For comparison sake, we applied the LORA model to the case study already done by Saranga (Saranga & al., 2006). In this experiment, the settings were chosen as described in (Saranga & al., 2006) on two echelon repair network for an aircraft engine with three-indenture structure. The optimal or near optimal solution obtained by Saranga' work and our GATS algorithm were found similar, only part 5 has got different repair decision (table 6.2). The total maintenance costs incurred are respectively 4255.274 and 4216.274.

The second important issue related to the optimisation problem is the computational time. The algorithms GATS is written in the MATLAB language and implemented on a Pentium 4 CPU 2.60 GHZ with 512 Mo RAM. The computing time required to solve the LORA problem varies with system structure (total number of items) and the repair network. Figure 6.7 represents the computing time taken to solve the problems for the data sets created randomly for 3 echelon network. For problem that has been discussed above, it took an average time of 21 seconds to solve the problems. As was previously mentioned, the solution representation is a (n x d) binary matrix, where n is the number of all parts under consideration and d the number of all repair decision throughout the repair network. The solution has for a system with n parts with m echelons and r_i repair options at echelon i, the number of possible solutions is equal to s^n.

Where: $s = \sum_{i=1}^{m} r_i$, r_i is the number of repair options at echelon i.

For a case study with 40 parts, the size of the solution space will be for 3 echelons as high as 2.14×10^{96}.

Table (6.2): Best LORA solution for Saranga's case study

Best solution obtained by Saranga's work

	echelon 1			echelon m	
	Repair	Discard	Move	Repair	Discard
Part 1	1	0	0	0	0
Part 2	0	0	1	0	1
Part 3	1	0	0	0	0
Part 4	0	1	0	0	0
Part 5	0	1	0	0	0
Part 6	0	0	1	0	1
Part 7	0	1	0	0	0
Part 8	0	0	1	0	1
Part 9	0	1	0	0	0
Part 10	0	1	0	0	0
Part 11	0	1	0	0	0
Part 12	0	1	0	0	0
Part 13	0	0	1	0	1
Part 14	0	0	1	0	1
Part 15	0	0	1	0	1
Part 16	0	1	0	0	0
Part 17	0	1	0	0	0
Part 18	0	1	0	0	0
Part 19	0	1	0	0	0
Part 20	0	1	0	0	0
Part 21	0	1	0	0	0
Part 22	0	1	0	0	0
Part 23	0	0	1	0	1
Part 24	0	0	1	0	1
Part 25	0	1	0	0	0
Part 26	0	1	0	0	0
Part 27	0	1	0	0	0
Part 28	0	1	0	0	0
Part 29	0	1	0	0	0
Part 30	0	1	0	0	0
Part 31	0	0	1	0	1
Part 32	0	1	0	0	0

Total maintenance costs = 4255.274

Best solution delivered by our GATS algorithm

	echelon 1			echelon m	
	Repair	Discard	Move	Repair	Discard
Part 1	1	0	0	0	0
Part 2	0	0	1	0	1
Part 3	1	0	0	0	0
Part 4	0	1	0	0	0
Part 5	1	0	0	0	0
Part 6	0	0	1	0	1
Part 7	0	1	0	0	0
Part 8	0	0	1	0	1
Part 9	0	1	0	0	0
Part 10	0	1	0	0	0
Part 11	0	1	0	0	0
Part 12	0	1	0	0	0
Part 13	0	0	1	0	1
Part 14	0	0	1	0	1
Part 15	0	0	1	0	1
Part 16	0	1	0	0	0
Part 17	0	1	0	0	0
Part 18	0	1	0	0	0
Part 19	0	1	0	0	0
Part 20	0	1	0	0	0
Part 21	0	1	0	0	0
Part 22	0	1	0	0	0
Part 23	0	0	1	0	1
Part 24	0	0	1	0	1
Part 25	0	1	0	0	0
Part 26	0	1	0	0	0
Part 27	0	1	0	0	0
Part 28	0	1	0	0	0
Part 29	0	1	0	0	0
Part 30	0	1	0	0	0
Part 31	0	0	1	0	1
Part 32	0	1	0	0	0

Total maintenance costs = 4216,274

A comparison between two and three echelon network computational time that takes LORA model to come out with the optimal solution is shown in (figure 6.7). The computational time increases exponentially with system structure size and the bigger the number of echelon is the higher the computing time is. Thus, researchers consider three echelon repair network is enough in practice to handle maintenance activities and to be modelled by acceptable computational time.

Let's consider maintenance support organisation MSO as responsible to provide the maintenance resources and closer support equipment to repair shops. Providing such equipment requires huge investment for systems. Therefore, it is crucial to design the needed amount of support resources to minimise whole life cost WLC. The developed model can rank the competing repair options for multi-indenture levels and multi-indenture system; and compute WLC measures in this ranking. The results of various repair decisions using the information of Table 6.1 leading to the minimum WLC are shown in Table 6.3.

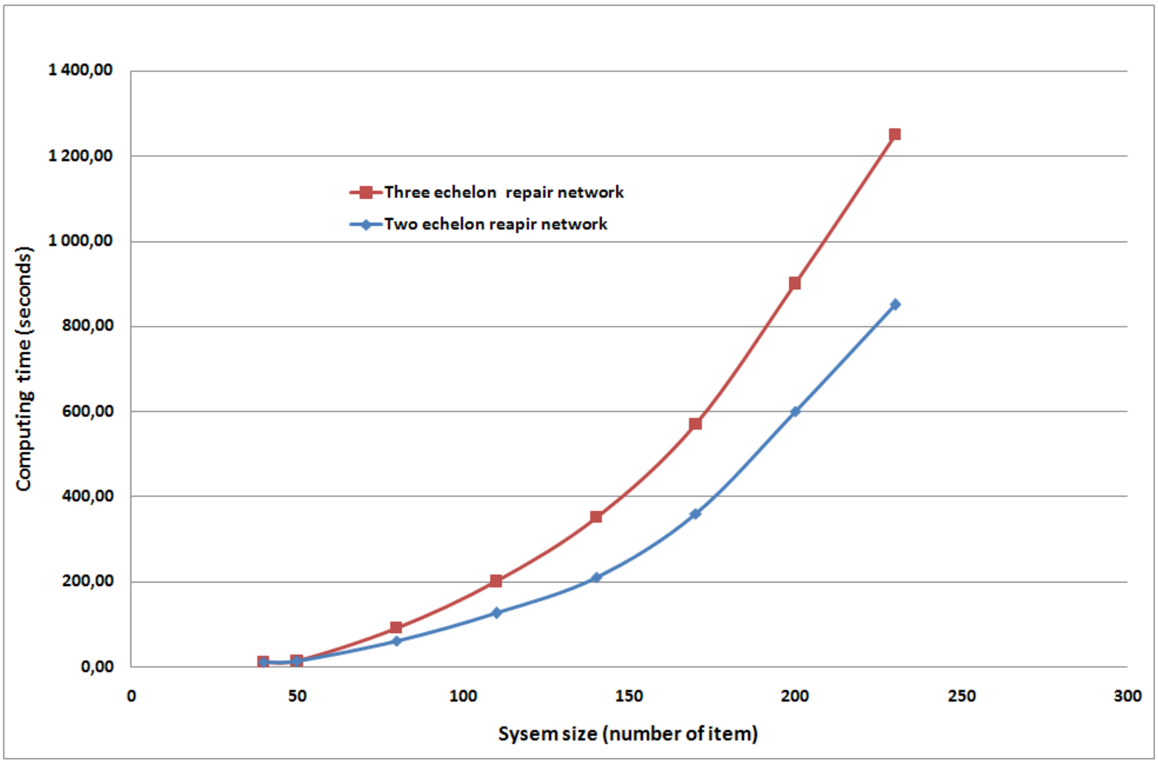

Fig. (6.7): LORA model computational time

As shown in Table 6.3, LORA decision is based on (0,1) matrix where the rows represent the items that constitute the system under study and the columns represent the locations where the items should be repaired, discarded or moved to higher repair echelon. These repair decisions (repair, discard and move) are designated by the following symbols: r, d and m respectively. For any echelon, the possible scenarios are as follow:

- When: r =1 and (d = m = 0) means that the item is going to repaired at this echelon.
- When: d =1 and (r = m = 0) means that the item is going to discarded at this echelon.
- When: m =1 and (r = d = 0) means that the item is going to repaired or discarded at higher echelons.

Since SONATRACH's repair shops are structured into three echelons, the number of possible repair scenario for system with 82 items is $4.23 * 10^{24}$ solutions. The optimal solution in terms of whole life costs of this combinatorial optimisation problem is delivered by the developed framework. Using repair cost data and item failure rates collected mainly from SONATRACH's maintenance records and in some cases from international petroleum database (OREDA) when the needed data is missing (Table 6.1), decisions where to repair system items are shown in Table 6.3. These LORA results provide maintenance logistics personnel with the list of items to repair or to discard at each repair echelon and the support resources required to make sure the repair tasks are done based on cost considerations and operational readiness requirements. This list is merely established by putting together items with value one at each echelon and for each repair decision (repair or discard) as shown in Table 6.3.

It can be noted that all first indenture subsystems (turnion support, air inlet etc.) are repaired at the repair echelon 1. The reason is that the reparation consists only in failed LRU isolation and, therefore, their repair tasks at echelon 1 are less costly compared to other echelons. In addition, all enclosure elements of compressor system, combustion system and turbine which represent the main gas turbine elements are repaired at the third repair echelon. This decision is the result of low repair costs at this echelon which is characterised by the heavily installed repair equipment and a high number of items to be repaired. This implies that repair cost per item at this echelon is the lowest in the repair network.

The allocation of items throughout repair network was also calculated and are summarised in Table (6.4). The number of items to be serviced by echelons 1, 2 and 3 will be 19, 15 and 48 respectively. 59% of items will move to the echelon 3 where major repair equipment is installed. The whole life repair cost of this optimal solution is 67 478.55. As shown in table 6.4, both the echelon 1 and 3 represent 36% and 38% of the repair WLC respectively. Besides, compared to repair configuration by SONTARACH, this solution achieve a cost reduction of 9.5% over the life span of a gas turbine, this reduction is worth millions of dollars.

Table (6.3): Lora model output

items	ECHELON 1			ECHELON 2			ECHELON 3	
	r	d	m	r	d	m	r	d
Turnion support	1	0	0	0	0	0	0	0
Air inlet	1	0	0	0	0	0	0	0
Evap cooler	1	0	0	0	0	0	0	0
Water system	1	0	0	0	0	0	0	0
Humid badges	0	1	0	0	0	0	0	0
Inlet piping	0	0	1	0	1	0	0	0
Mesh	1	0	0	0	0	0	0	0
Filter system	0	0	1	0	1	0	0	0
Mufflersystem	0	0	1	1	0	0	0	0
Radial inflow inlet casing	0	0	1	0	1	0	0	0
Compressor system	1	0	0	0	0	0	0	0
Blade system	0	0	1	0	0	1	1	0
Blade ring	0	0	1	0	0	1	0	1
Rotor blade	0	0	1	0	0	1	0	1
Variable inlet guide vane	0	0	1	0	0	1	1	0
Shaft	0	0	1	0	0	1	1	0
Rinsing system	0	0	1	0	0	1	0	1
Pump	0	0	1	0	0	1	0	1
Water ejector	0	0	1	0	0	1	0	1
Detergent reservoir	0	0	1	0	0	1	0	1
Piping	0	0	1	0	0	1	0	1
Extraction system	0	0	1	0	0	1	1	0
Low pressure	0	0	1	0	0	1	0	1
High pressure	0	0	1	0	0	1	0	1
Journal bearing	0	0	1	0	0	1	1	0
Lubrication system	0	0	1	0	0	1	0	1
Casing	0	0	1	0	0	1	1	0
Thermocouple	0	0	1	0	0	1	1	0
Pad	0	0	1	0	0	1	0	1
Casing system	0	0	1	0	0	1	1	0
Stationary blade	0	0	1	0	0	1	1	0
Casing	0	0	1	0	0	1	0	1
Trust bearing	0	0	1	0	0	1	1	0
Lubrication system	0	0	1	0	0	1	0	1
housing	0	0	1	0	0	1	1	0
Shoes	0	0	1	0	0	1	1	0
Filter ring	0	0	1	0	0	1	1	0
Thermocouples	0	0	1	0	0	1	0	1
Load equalizing	0	0	1	0	0	1	1	0
Combustion system	1	0	0	0	0	0	0	0
Igniter system	0	0	1	0	0	1	0	1
Piston	0	0	1	0	0	1	0	1
Igniter	0	0	1	0	0	1	0	1
Spring	0	0	1	0	0	1	0	1
Combustor shell extract.	0	0	1	0	0	1	1	0
Disk cavt 2 cooling	0	0	1	0	0	1	1	0
Disk cavt 3 cooling	0	0	1	0	0	1	1	0
Vane cooling	0	0	1	0	0	1	1	0
Combustor shell	0	0	1	0	0	1	1	0
Combustor cylinder	0	0	1	0	0	1	1	0
Combustion basket	0	0	1	0	0	1	0	1
Cross flame	0	0	1	0	0	1	1	0
Cooling system	0	0	1	1	0	0	0	0
Bypass valve	0	0	1	0	0	1	0	1
Control system	0	0	1	0	0	1	0	1
Piping	0	0	1	0	0	1	0	1
Turbine	1	0	0	0	0	0	0	0
Vane system	0	0	1	1	0	0	0	0
Thermocouple	0	0	1	1	0	0	0	0
Vanes	0	0	1	0	0	1	0	1
Vane pin	0	0	1	0	0	1	0	1
Cylinder Turbine	1	0	0	0	0	0	0	0
Blade rings	0	1	0	0	0	0	0	0
Blade pin	0	1	0	0	0	0	0	0
blades	0	0	1	0	1	0	0	0
Shaft	0	0	1	1	0	0	0	0
Radial Bearing	0	0	1	1	0	0	0	0
Thermocouple	0	0	1	1	0	0	0	0
Pads	0	0	1	1	0	0	0	0
Lubrication system	0	0	1	1	0	0	0	0
Shell	0	0	1	0	0	1	0	1
Exhaust	0	0	1	1	0	0	0	0
Exhaust collector	0	0	1	0	0	1	0	1
Exhaust cylinder	0	0	1	1	0	0	0	0
Exhaust connection	0	0	1	0	0	1	0	1
Turning gear	1	0	0	0	0	0	0	0
Turning gear	0	1	0	0	0	0	0	0
Electric Motor	0	1	0	0	0	0	0	0
Gear box	0	1	0	0	0	0	0	0
Start-up system	0	1	0	0	0	0	0	0
Electric Motor	0	1	0	0	0	0	0	0
Torque converter	0	1	0	0	0	0	0	0

Table (6.4): Lora model output

	ECHELON 1			ECHELON 2			ECHELON 3	
	r	d	m	r	d	m	r	d
Number of items	10	9	63	11	4	48	21	27
Number of items %	12.20%	10.98%	76.83%	13.41%	4.88%	58.54%	25.61%	32.93%
Cost	5 190.98	8 996.17	10 432.12	6 959.43	2 888.54	7 688.34	9 757.81	15 565.17
Cost %	7.69%	13.33%	15.46%	10.31%	4.28%	11.39%	14.46%	23.07%

After the selection of repair locations was completed, the next step of the LORA study was to conduct sensitivity analysis to show the robustness of the optimal solution. Sensitivity analysis is a modelling technique that is used to identify the impact of a change in input parameters on the optimal repair configuration. Based on the above solution, all demand parameters and costs of selected repair options will be increased until the optimal solution changes. Parameters leading to change in the optimal solution with the minimum variation will be considered the most sensitive variable.

The optimal solution is based on the following objective function:

$$\sum_{i=1}^{n}\sum_{r=1}^{3}\sum_{e=1}^{m}(VC_{r,e,i} * \lambda_i + FC_{r,e,i}) * X_{r,e,i}$$

Where: λ_i : failure rate of item i and also known in the practice by repair demand of item i.

$X_{r,e,i}$: *is* the repair decision integer variable i = {*0,1*}.

FC : fixed cost of repair actions,

VC: variable cost of repair actions per failure rate or repair demand.

The sensitivity analysis outcome is the change of the optimal solution with respect to changes in an input parameter. Because the units of measure of different parameters (VC, FC, λ_i and $X_{r,e,i}$) are not comparable, so absolute changes with respect to changes in different parameters are not used. One can often overcome this problem by calculating elasticities, which are measures of the percentage change in an input variable = $\frac{\Delta Y}{Y}$. A comparison of optimal solution change with respect to different parameter elasticities provides a good indication of the parameters to which the LORA decision is most sensitive. Table 6.5 is an example of such a comparison for LORA output by answering the following questions: If parameter Y were to change from its current value, by how much would it have to change in order for the optimal solution to change in a particular way. These breakeven results, calculated by one of the developed framework model, have been obtained by increasing any parameter elasticity until the actual optimal solution changes. Conducting this sensitivity analysis, three main conclusions have been drawn:

- If a threshold of 30% is set for the comparison, items with breakeven elasticities less than 30% are considered the most sensitive item in the optimal repair configuration and need more attention in estimating their input values.
- Items with breakeven elasticities greater than 30% are considered to have a minor impact on the optimal LORA solution.
- Failure rate (or repair demand) and variable cost have the same breakeven elastcicities for all items. The reason for that these two parameters appear in the objective function with multiplication factor. This means a relative increase (%) in $\mathrm{VC}_{r,e,i}$ has the same effect on $\mathrm{VC}_{r,e,i} * \lambda_{\mathrm{i}}$ as the relative increase (%) in λ_{i}.

Lack of needed data is always considered a problem for techniques such as WLC and ILS. First of all there are problems with getting access to operational data with sufficient quality. The developed framework is very valuable in assessing the uncertainty linked to input data and its effect on the final LORA output. The framework results for sensitivity analysis given in Table 6.5 forms a very sound basis for deciding on input data that the framework users should give more attention in data collection and estimation in order to achieve comprehensive repair decisions.

For SONATRACH case study, casing and trust bearing items are found to be the most sensitive variable in the optimal repair configuration; an increase between 2.27% and 2.90% of their repair costs and repair demand (failure rate) data has led to a change in repair configuration. On the other hand, the radial inflow inlet casing item is found to be the most insensitive item with around 130% increase of its related LORA data that can result in change of repair configuration.

Table (6.5): Lora sensitivity analysis

items	Fixed Costs	Variable Costs	Repair Demand
Turnion support	29.22%	41.16%	41.16%
Air inlet	6.26%	6.03%	6.03%
Evap cooler	32.04%	37.27%	37.27%
Water system	14.53%	12.16%	12.16%
Humid badges	13.58%	9.67%	9.67%
Inlet piping	35.28%	29.14%	29.14%
Mesh	173.96%	98.25%	98.25%
Filter system	11.91%	10.90%	10.90%
Muffler system	71.53%	84.41%	84.41%
Radial inflow inlet casing	132.89%	129.24%	129.24%
Compressor system	83.51%	79.01%	79.01%
Blade system	92.08%	106.53%	106.53%
Blade ring	80.24%	78.62%	78.62%
Rotor blade	26.50%	26.38%	26.38%
Variable inlet guide vane	49.60%	56.30%	56.30%
Shaft	87.58%	101.91%	101.91%
Rinsing system	42.94%	52.24%	52.24%
Pump	12.29%	10.56%	10.56%
Water ejector	48.89%	47.80%	47.80%
Detergent reservoir	45.89%	49.70%	49.70%
Piping	39.69%	57.85%	57.85%
Extraction system	9.39%	14.11%	14.11%
Low pressure	98.20%	98.08%	98.08%
High pressure	69.42%	88.85%	88.85%
Journal bearing	101.75%	96.13%	96.13%
Lubrication system	71.38%	84.01%	84.01%
Casing	90.66%	108.31%	108.31%
Thermocouple	17.02%	17.42%	17.42%
Pad	16.47%	18.22%	18.22%
Casing system	16.42%	17.75%	17.75%
Stationary blade	14.93%	19.41%	19.41%
Casing	**2.73%**	**2.27%**	**2.27%**
Trust bearing	**2.43%**	**2.90%**	**2.90%**
Lubrication system	84.24%	123.12%	123.12%
housing	84.43%	119.00%	119.00%
Shoes	27.56%	41.50%	41.50%
Filter ring	8.95%	12.53%	12.53%
Thermocouples	40.16%	59.34%	59.34%
Load equalizing	76.61%	50.98%	50.98%
Turning gear	**4.43%**	**2.53%**	**2.53%**
Turning gear	**4.17%**	**2.47%**	**2.47%**
Electric Motor	**3.99%**	**2.59%**	**2.59%**
Gear box	102.53%	74.71%	74.71%
Start-up system	29.61%	24.61%	24.61%
Electric Motor	82.04%	89.93%	89.93%
Torque converter	26.04%	28.65%	28.65%

items	Fixed Costs	Variable Costs	Repair Demand
Combustion system	43.86%	31.17%	31.17%
Igniter system	44.35%	30.92%	30.92%
Piston	31.57%	34.97%	34.97%
Igniter	13.89%	7.86%	7.86%
Spring	115.44%	69.50%	69.50%
Combustor shell extract.	43.71%	26.69%	26.69%
Disk cavt 2 cooling	110.16%	64.40%	64.40%
Disk cavt 3 cooling	**2.66%**	**2.70%**	**2.70%**
Vane cooling	11.83%	9.97%	9.97%
Combustor shell	12.38%	10.16%	10.16%
Combustor cylinder	40.93%	33.16%	33.16%
Combustion basket	47.66%	29.47%	29.47%
Cross flame	46.04%	29.85%	29.85%
Cooling system	38.29%	32.81%	32.81%
Bypass valve	106.54%	90.79%	90.79%
Control system	**3.72%**	**2.05%**	**2.05%**
Piping	103.08%	93.94%	93.94%
Turbine	**3.20%**	**3.08%**	**3.08%**
Vane system	101.94%	94.83%	94.83%
Thermocouple	105.56%	93.85%	93.85%
Vanes	**4.28%**	**2.61%**	**2.61%**
Vane pin	129.64%	79.74%	79.74%
Cylinder Turbine	129.38%	79.86%	79.86%
Blade rings	43.52%	31.61%	31.61%
Blade pin	13.92%	9.23%	9.23%
blades	13.69%	9.19%	9.19%
Shaft	123.96%	82.08%	82.08%
Radial Bearing	109.38%	90.06%	90.06%
Thermocouple	96.44%	100.15%	100.15%
Pads	76.00%	80.06%	80.06%
Lubrication system	29.83%	30.86%	30.86%
Shell	41.16%	24.15%	24.15%
Exhaust	85.31%	71.04%	71.04%
Exhaust collector	87.04%	69.98%	69.98%
Exhaust cylinder	85.09%	70.65%	70.65%
Exhaust connection	34.33%	27.12%	27.12%

6.6 SUMMARY

A typical level of repair analysis including multiple repair facilities and system of thousands items is formalised by Integer Programming (IP) model. Traditional optimisation techniques cannot be effectively applied to solve LORA models for real-world applications in which systems may enclose millions of parts. In this chapter, a hybrid algorithm of Genetic Algorithm and TABU Search (GATS) has been developed and implemented into a computational algorithm in MATALAB code to solve this mathematical formulation. The algorithm adopts a matrix representation for the system breakdown structure to handle the constraint linking parent items and children items. The efficacy of the algorithm has been validated in the context of two examples. The repair decision of all system items has been optimised for a structure of 3 echelon repair network and multi-indenture system. The results have shown that quite large LORA optimisation can be obtained in realistic times, demonstrating that the algorithm is practical. Besides, the robustness of the optimal solution has been demonstrated through sensitivity analysis. Item parameters which are the most sensitive to repair configuration have been identified for further examination.

There are some practical issues that need to be addressed, however. This LORA problem optimises maintenance costs based only on repair facilities. This should be extended to include other maintenance costs such as spare part provision. Further research in this area will include studying the impact of both spare part provision and repair facilities on LORA problems. Besides, spare part optimisation under finite repair capacity is being integrated into the development of the algorithm and will be reported in chapter 8.

CHAPTER 7 SPARE PART MANAGEMENT MODEL

7.1 INTRODUCTION

In Chapter 4, the mathematical model for spare part inventory management has been introduced to evaluate the optimal inventory of two particular repair options: 1) the infinite repair capacity and 2) the limited repair capacity based on queuing theory. Besides, the model has been extended to the multi-echelon, multi-indenture system with commonality. Petroleum companies, alike SONATRACH, usually have a central repair shop where most needed spare parts are stored. Additionally, they also install dispersed local shops near the operation sites for quick maintenance services. Generally, when a system is malfunctioning, maintenance crew carries out inspections to isolate defective components. These parts are then sent out for repair and a request for ready-for-use ones is issued. Holding enough spare parts at local shops ensures two advantages. The probability that failed components will be replaced immediately increases and as a result the cost of repair delays will be reduced along with client satisfaction. In addition transportation cost between the central shop and local ones will be minimised. However, this inventory policy may be inappropriate in practice when installed systems and their enclosed parts are very expensive. Therefore, companies are constantly looking for a trade-offs between operation requirements and inventory holding cost. This chapter presents and analyses spare mixes generated by the model and how they change with regard to the installed repair capacity.

In the following section, a review of the developed spare part models is presented. Next, the model is demonstrated in the context of case studies in section 7.3. Then, an additional algorithm is proposed to handle the impact of repair capacity on spare part inventory in section 7.4. A summary of chapter findings is presented in Section 7.5.

7.2 REVIEW OF THE DEVELOPED SPARE PART MODELS

This section presents the key aspects of the considered model. First, the model will be used to generate spares mixes for the three following situations: (1) single-indenture single-echelon model, (2) multi-indenture single-echelon model and (3) multi-indenture multi-echelon model. Then, an analysis of the model performance for these situations is provided. Next, the effect of repair capacity on model outputs is highlighted.

In this chapter, the inventory model serving K installed systems is analysed. For each installed system, i.e., a gas turbine consisting of N items having a subscript $i \in \{1, 2, \ldots, N\}$, the stock levels at all warehouses is determined such as to keep the average system availability above a given threshold while minimising spare part cost. Firstly, this section explores the effectiveness of each inventory model developed in sections 4.4. The performance of the multi-echelon model against the single-echelon model is then compared in terms of holding cost and computational time for given availability values.

Basically, the model is founded on the fact that a failed item is replaced by a new one from the stock in hand if one is available; otherwise, the system is inactive until a required item is repaired by local repair shop or supplied from stocks. When they failed item is sent out for repair at the nearest shop, the latter immediately generates a request for a functional item from the stocks. This item is generally provided without delay; if not, the first available one from the repair shop is delivered. The number of unfilled requests, i.e., the number of demands that have not been satisfied at any point in time, is called the expected backorders (EBOs) given by the following equation:

$$E[BO_i(S_i)] = \sum_{S_i+1}^{\infty} (x - S_i) * P(BO_i > 0) \qquad (7.1)$$

Where:

x_i is the pipeline inventory of item i;

S_i the stock on hand of item i;

P(BOi): the probability that there is a request for a new items.

On the other hand, the probability that systems are not operational for any spare is given by the following system Availability, A:

$$A = \prod_{i=1}^{N} (1 - \frac{EBO_i(S_i)}{Z_i})^{Z_i} \qquad (7.2)$$

Where:

$$\text{the difference } \left(1 - \frac{\mathrm{EBO_i(S_i)}}{\mathrm{Z_i}}\right) \text{represents the availability of item i.}$$

The models calculate inventory levels by using an objective function that is the availability maximisation for installed systems which can be replaced by backorder minimisation at local bases for all first indenture components (chapter 4). Therefore, inventory optimisation can be written as:

Problem P:

$$\begin{cases} \min \sum_{i=1}^{\mathrm{ech(N)}} \sum_{j=1}^{\mathrm{ind(1)}} \mathrm{BO_{ij}}\left(\mathrm{S_{ij}}\right) \\ \text{Subjet to} \\ \mathrm{S_{ij}} \geq 0 \\ \sum_{i=1}^{n} \mathrm{c_i} \sum_{j=1}^{\mathrm{ech(N)}} \mathrm{S_{ij}} \leq \text{Budget} \end{cases} \tag{7.3}$$

Based on the backorder definition (equation 7.1), it is clear to notice that Bi(Si) decreases as stock level increases. Therefore, this objective function of problem P is a convex function. This property allows optimising the problem P by allocating an item to the warehouses that presents the maximum decrease in the objective function per unit cost. This step will be repeated until the budget limit is reached.

7.2.1 MODEL ASSUMPTIONS

The following hypotheses are considered for the model assumption:

- The repair network has a treelike structure. That is, each warehouse is supplied from one base at higher echelon. At the top of the repair network, there is only one central base (figure 4.6).
- The demands for item replacement and repair only take place at the repair shops at the lowest echelon.

- The failure processes at all bases are independent Poisson process and the coefficients are known and stationary.
- The unfulfilled demands will be backordered.
- The repair shops have an infinite capacity working on first-come-first-serve policy.

7.3 EXPERIMENTAL RESULTS

In the following computational experiment, a gas turbine comprising more than 80 line repair units (LRUs) as illustrated in Figure 4.2 is analysed. A number of the installed systems are supported by local repair shops which in turn are supported by other ones located at next higher echelon. To provide the required system supportability, a local Maintenance Support Organisation (MSO) is in charge for material and personnel deployment between all repair shops under its responsibility. The following three sets of experiments have been carried out to estimate how many spare parts MSO should be kept at the repair shops to respond to the operational requirement. These experiments are:

- Single-indenture single-echelon (SI-SE) model,
- Multi-indenture single-echelon (MI-SE) model,
- Multi-indenture multi-echelon (MI-ME) model.

Besides, the performance of these three approximation models is evaluated in terms of: inventory budget with respect to availability threshold, the estimated availability values at a fixed inventory cost, and computational time.

7.3.1 PROBLEM FORMULATION

A repair network consisting of m local repair shops and a central depot is considered (Figure 7.1). All support warehouses apply continuous stocking policy based on (S-1, 1) rule. The item failure follows a Poisson process with failure rate λ and is fulfilled on a First Come First Serve FCFS policy. These hypotheses are realistic for high value and low demand parts as it is the case in SONATRACH Parts assortment.

There are two repair echelons. The first echelon has only one base called central base or central depot. This depot is replenished from external suppliers with a mean supply time, which is around 0.76 year. The second echelon has two local bases supplied by the central depot. The mean transportation time between the two echelons is 0.2 year. The mean service time or repair time are different at different bases. Table 7.1 presents field data used in this study. In the table, the first row is the repair demand value for first

Table (7.1): Model input data

Item	1	2	3	4	5	6	7	8	9	10	11	12	13	14
repair demand λ_i	3,11	2,29	3,26	3,27	4,28	4,22								
cost c_i	0,53	0,65	1,33	0,88	1,27	0,90	0,08	0,04	0,08	0,08	0,08	0,08	0,08	0,05
Mean repair time at local bases	0,03	0,03	0,03	0,03	0,03	0,03	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02
repair probability at local bases	0,85	0,84	0,82	0,87	0,85	0,87	0,21	0,21	0,20	0,22	0,21	0,20	0,21	0,21
repair probability at central base	0,05	0,05	0,05	0,05	0,05	0,05	0,73	0,72	0,71	0,77	0,73	0,71	0,75	0,73
Mean procurement time from item suppliers	0,80	0,78	0,75	0,77	0,78	0,76	0,55	0,50	0,51	0,52	0,52	0,55	0,54	0,51
Mean repair time at central base	0,03	0,03	0,03	0,03	0,03	0,03	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02
Mean transport time between bases	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20

Item	15	16	17	18	19	20	21	22	23	24	25	26	27	28
repair demand λ_i														
cost c_i	0,06	0,05	0,06	0,06	0,05	0,05	0,06	0,07	0,05	0,06	0,06	0,06	0,06	0,06
Mean repair time at local bases	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02
repair probability at local bases	0,20	0,21	0,21	0,21	0,20	0,20	0,21	0,21	0,21	0,21	0,22	0,21	0,22	0,22
repair probability at central base	0,70	0,74	0,74	0,75	0,71	0,72	0,74	0,73	0,74	0,73	0,77	0,73	0,77	0,77
Mean procurement time from item suppliers	0,52	0,50	0,53	0,52	0,55	0,53	0,53	0,51	0,54	0,51	0,51	0,51	0,52	0,51
Mean repair time at central base	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02
Mean transport time between bases	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20

Item	29	30	31	32	33	34	35	36	37	38	39	40	41
repair demand λ_i													
cost c_i	0,06	0,00	0,00	0,01	0,01	0,01	0,01	0,00	0,00	0,01	0,00	0,00	0,00
Mean repair time at local bases	0,02	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
repair probability at local bases	0,22	0,21	0,22	0,21	0,21	0,20	0,21	0,21	0,21	0,20	0,22	0,22	0,21
repair probability at central base	0,76	0,73	0,76	0,73	0,73	0,71	0,75	0,73	0,75	0,71	0,76	0,76	0,75
Mean procurement time from item suppliers	0,50	0,33	0,32	0,33	0,32	0,32	0,30	0,32	0,30	0,31	0,32	0,33	0,32
Mean repair time at central base	0,02	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
Mean transport time between bases	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20

Item	42	43	44	45	46	47	48	49	50	51	52	53	54	55
repair demand λ_i														
cost c_i	0,00	0,00	0,01	0,00	0,01	0,01	0,01	0,00	0,01	0,01	0,01	0,01	0,01	0,01
Mean repair time at local bases	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
repair probability at local bases	0,21	0,21	0,22	0,21	0,20	0,21	0,21	0,22	0,21	0,22	0,21	0,21	0,21	0,20
repair probability at central base	0,75	0,74	0,75	0,73	0,72	0,72	0,74	0,76	0,72	0,77	0,73	0,75	0,73	0,71
Mean procurement time from item suppliers	0,30	0,30	0,31	0,31	0,32	0,30	0,32	0,32	0,31	0,30	0,30	0,31	0,31	0,33
Mean repair time at central base	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
Mean transport time between bases	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20

Item	56	57	58	59	60	61	62	63	64	65	66	67	68	69
repair demand λ_i														
cost c_i	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
Mean repair time at local bases	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
repair probability at local bases	0,20	0,21	0,21	0,22	0,20	0,21	0,20	0,20	0,21	0,21	0,22	0,20	0,21	0,20
repair probability at central base	0,71	0,73	0,74	0,77	0,71	0,75	0,72	0,71	0,75	0,73	0,76	0,70	0,72	0,71
Mean procurement time from item suppliers	0,33	0,32	0,33	0,32	0,31	0,32	0,32	0,33	0,31	0,31	0,30	0,32	0,32	0,30
Mean repair time at central base	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
Mean transport time between bases	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20

Item	70	71	72	73	74	75	76	77	78	79	80	81	82
repair demand λ_i													
cost c_i	0,01	0,01	0,01	0,01	0,01	0,00	0,01	0,01	0,01	0,01	0,01	0,01	0,01
Mean repair time at local bases	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
repair probability at local bases	0,20	0,21	0,22	0,20	0,21	0,22	0,21	0,20	0,22	0,21	0,21	0,21	0,22
repair probability at central base	0,70	0,73	0,77	0,71	0,75	0,77	0,72	0,72	0,76	0,73	0,74	0,74	0,77
Mean procurement time from item suppliers	0,31	0,30	0,32	0,30	0,32	0,32	0,30	0,30	0,30	0,31	0,31	0,31	0,32
Mean repair time at central base	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
Mean transport time between bases	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20	0,20

Table (7.2): Commonality Matrix

item	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0,39	0,14	0,11	0,13	0,13	0,11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0,18	0,17	0,15	0,15	0,15	0,20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0,31	0,28	0,20	0,20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,23	0,17	0,22	0,19	0,19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,53	0,47	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,56	0,44	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,35	0,24	0,20	0,20	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,19	0,19	0,19	0,42	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,50	0,50	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,15	0,29
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

item	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0,28	0,28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0,63	0,37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0,17	0,17	0,17	0,12	0,21	0,17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0,30	0,44	0,27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0,33	0,33	0,35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,36	0,36	0,28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,31	0,34	0,34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,42	0,32	0,25	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,26	0,26	0,47	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,25	0,25	0,25	0,25	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,37	0,29	0,33	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,50	0,50	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,50	0,50

indenture items. The next row contains the procurement cost and the following six rows display the repair probability, mean reparation time and mean transport time for the central depot and local bases respectively. Other parameters involved in the problem include the commonality matrix which shows the proportion of the failure of parent components caused by their children items (Table 7.2). Parent components appear in rows and children items are presented in columns. For instance, failure of item 2 is the result of the failure of its six children (7, 8, 9, 10, 11 and 12). The probabilities that one of these children has caused the failure of item 2 are: 0.39, 0.14, 0.11, 0.13, 0.13, and 0.11 respectively.

7.3.2 RESULT ANALYSIS AND DISCUSSION

The analysis started by verifying backorder convexity, a compulsory condition for greedy algorithm, to solve the problem P. As it is shown in Figure 7.1, backorder probability decreases for any increase in the stock level. For this reason, the greedy marginal procedure is the most advocated in the literature to optimise inventory cost (Sherbrooke, 1968 and Graves, 1985). As stated before, this procedure adds to the inventory level in each iteration one unit of a selected item until the required service level is fulfilled. Deciding which item to select is based upon the relative increase of the system availability in relation to the inventory cost increase. As it can be seen from the backorder curves, when the stock level is greater than 6 units for each item, there are no backorders as a result, the system availability approaches the asymptotic value of one.

Since backorder is convex, the greedy approach optimisation as described above has been applied by considering infinite repair capacity. The problem solution is obtained until the availability is reached 99.99%. In this example, 530 possible solutions have been examined for each considered model. Besides, all these possible solutions represent the optimal pairs (inventory cost C, system availability A) for which any invested dollar have led to the maximum increase in system availability. These pairs constitute a so-called spare part investment versus availability curve; they are graphically depicted in figure 7.2. These Numerical comparisons are given in this section to evaluate the performances of the three models with respect to holding cost for a given availability value. The figure 7.2 presents the corresponding optimisation curves for the three aforementioned situations (single-indenture single-echelon model, multi-indenture single-echelon model

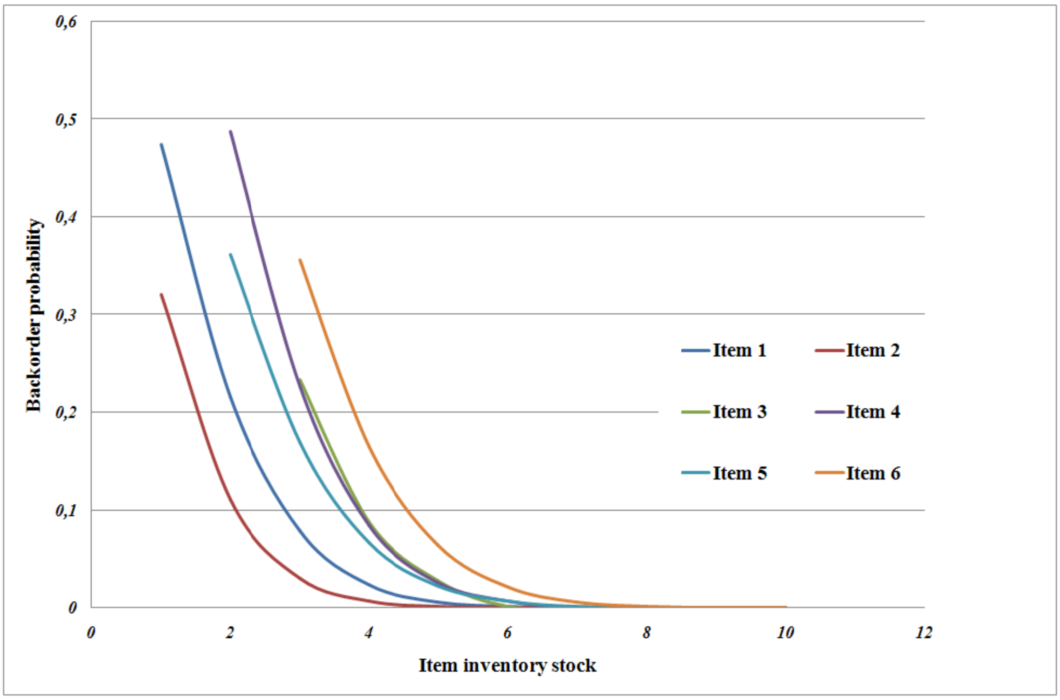

Fig. (7.1): Backorder probability as function of stock levels

and multi-indenture multi-echelon model).The results for the case study show that all the mutli-indenture models clearly outperform single-indenture model and their relative cost difference is quite important.

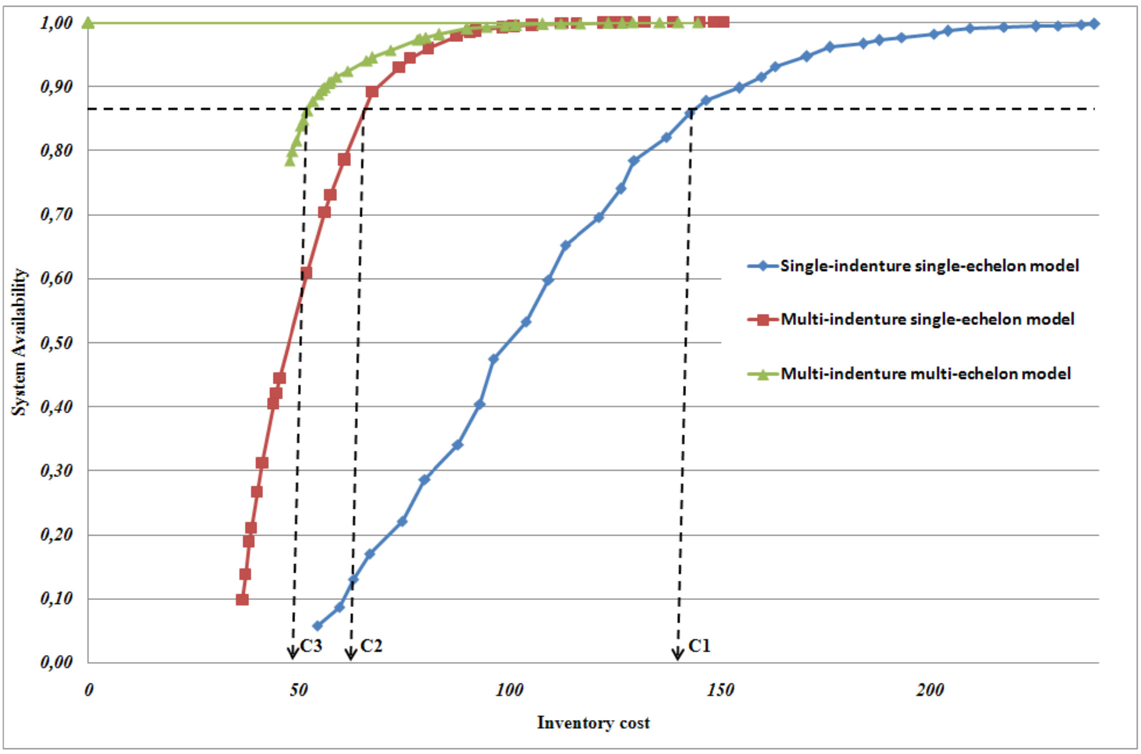

Fig. (7.2): Availability vs. Cost curve for given repair network

Figure 7.2 and table 7.3 demonstrate that the single-indenture single-echelon model overestimates the inventory holding costs. In particular, expensive system components may result in overestimation of the spare part cost associated with a given availability level. Consequently, the single-indenture single-echelon model is not considered as a cost-effective approach for spare part management. When the number of indentures and echelons increases, better approximation for inventory level can be achieved. As shown in table 7.3, the holding cost reduction when multi-indenture single-echelon model is considered varies from 54.78% to 56.36%. This reduction can attain 63.65% if inventory level is estimated by multi-indenture multi-echelon model.

Table (7.3): Comparison results

	MI-SE model vs. SI-SE model		MI-ME model vs. SI-SE model		MI-ME model vs. MI-SE model	
Availability	C1-C2	%	C1-C3	%	C2-C3	%
86%	78.14	54.78%	90.59	63.51%	12.45	19.30%
90%	7.11	56.36%	98.38	63.65%	11.27	16.71%
95%	4.17	55.20%	100.87	59.12%	6.70	8.76%
99%	19.01	56.83%	119.38	57.01%	0.37	0.41%

On the other hand, the analysis indicates that the performance in the multi-echelon model is much better than in the single-echelon case; this illustrates the effectiveness of repair arborescent structure. Actually, less spare parts are needed for two-level repair structure since there is a reduction in the turnaround time of failed items. The repair of gas turbines is a particularly complex and difficult task that needs skilled repairmen along with specialized equipment. Besides, the repair of these systems may be performed local bases, in that way entailing duplication of repair equipment across the repair network. This configuration has the advantage that the turnaround times for failed items are quick; as a result, the spare parts necessary to support maintenance are small. Nevertheless, it has the disadvantage that it is extremely expensive to operate.

7.4 INVENTORY OPTIMISATION UNDER LIMITED REPAIR CAPACITY

Thus far, repair resources have been assumed to be unlimited which, of course, is not realistic. This section describes how the model estimates the inventory level when repair resources are made up of a set of servers. Figure 7.3 depicts the availability vs. spare cost curve for different repair capacity. It is clear that additional investment in repair capacity (increasing the number of repair servers) results in a decrease in the inventory cost for the same availability values. In the case of infinite repair capacity, the purple line represents the asymptote from which no further reduction in inventory cost is achieved by increase in repair capacity. Besides, this asymptote is almost identical to that obtained with 4 repair servers. Therefore, it is not worth envisaging more than 4 repair servers per repair shop. For a given availability values, asset managers can decide whatever to repair failed items or to possess enough spares for immediate replacements.

For instance, the difference inventory investment (C3-C1) for the same availability may increase to 46.2%. Alternatively, the benefit in inventory investment is approximately 20 when there are more additional repair servers. Therefore, the question is: given the availability threshold value, what is the cost effective investment decision in repair capacity vs. inventory? The answer is summarized in table 7.4 for the 1, 2, 4 and infinite repair capacity, respectively. The percent differences of the inventory cost reduction are used as performance to measure any decision to invest in repair capacity.

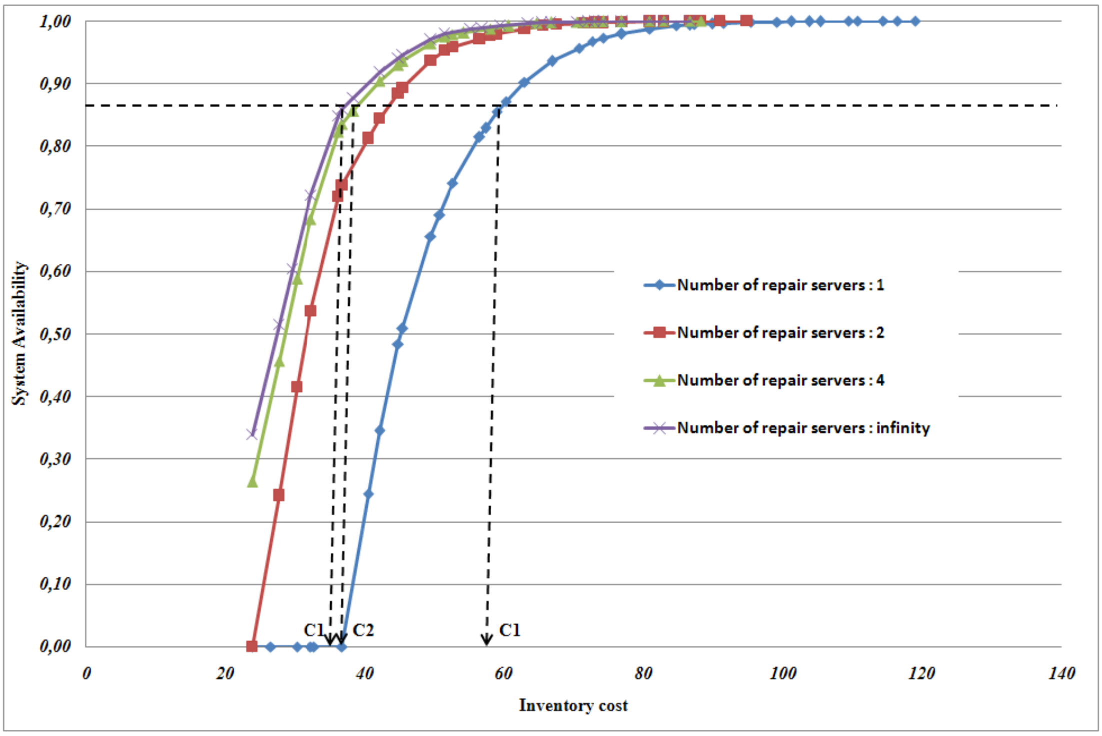

Fig. (7.3): Availability vs. Cost curve for given repair capacity

Compared to 1 server repair capacity case, it has been found that the average percent reduction in inventory cost is around 39% for 2 server case and around 45% for the other cases. The maximum observed reduction is 46.2% for infinite repair case. However, the highest marginal reduction is achieved for 2 server case.

Table (7.4): Model comparison results

Availability	70%	80%	85%	90%	95%	99.99%
2 repair servers	38.9%	34.3%	38.8%	38.4%	39.2%	43.9%
4 repair servers	44.4%	42.8%	40.0%	41.1%	45.7%	46.2%
Infinite repair server	44.4%	43.1%	40.0%	41.1%	45.6%	46.2%

Finally, the main conclusions of this experiment are:

- The proposed algorithm generates the optimal spare level based on desired system availability and available budget;
- The repair shops are modelled as multi-server M/G/K queue model;
- Support costs (repair cost and spare part cost) are traded-off to achieve the most effective maintenance support decision.

7.5 SUMMARY

This chapter highlighted the advantage to achieve maintenance by the adoption of integrated logistics support elements. More specifically, in spare parts management for identical equipment installed in different geographical areas requiring very close repair services, a multi-echelon repair network is considered in this chapter that includes an arborescent repair structure. The results discussed show the impact of spare part modelling on the desired system availability. It was demonstrated that the queuing theory could provide an opportunity to better estimate the required spare parts and especially if the repair shops have a limited capacity. The study also reveals the trade-off between the spares inventory and investment in repair facilities. An underestimation of 40% in inventory cost for a given availability level when infinite repair capacity assumption is considered has been found. Future development of this study is to extend the models considered in this chapter to level of repair analysis technique. This extension can be used to refine the evaluation of inventory level and to replicate what is really experienced in practice. The integration of LORA model and spare part inventory model is reported in chapter 8.

CHAPTER 8 JOINT OPTIMISATION OF SPARE PART LEVEL AND LEVEL OF REPAIR ANALYSIS

8.1 INTRODUCTION

The traditional level of repair analysis LORA approach assumes that spare parts are always available as required and then repair costs are minimised throughout the repair network. Similarly, the traditional inventory approach considers ample repair capacity and then holding inventory costs are optimised with regard to desired service level. The two approaches are usually considered and optimised separately. However, these two aspects of integrated logistics support ILS do have an interaction impact on each other and consequently need to be optimised jointly for enhancing the maintenance support performance. For instance, when the repair capacity is small, the repair lead time could be very long; hence, a safety inventory should be needed during the lead time (Sleptchenko et al. 2002, 2003). Therefore, any reduction in repair capacity results is more required than spare parts and vice versa. In this chapter, a model is developed for integrating LORA and inventory control approaches. Its focus is on optimal maintenance support decisions for multi-echelon multi-indenture system that minimises whole life costs.

In Section 2, a brief background of relevant literature is presented. In Section 3, the problem formulation is discussed. Section 4 illustrates the need of joint optimisation through an example. The algorithm for joint optimisation of LORA problem and spare part optimisation is provided in section 5. Besides, this section is divided into three parts. First part provides a mathematical model for sequential optimisation, second part provides an iterative optimisation model, and third part discusses the integrated model. In Section 6, the evaluation methodology and results for these three parts are presented. Finally, Section 7 presents the concluding remarks of this chapter.

The ability to reduce system downtime is crucial for time-sensitive industrial activities. To guarantee the throughput of such activities, system repair should be cost-effective, based on prompt related-support activities. Especially, repair tasks and the spare part inventory should be optimised to support systems in satisfying a certain level of operation at the lowest whole life cost. Inventory optimisation has been studied extensively in the literature, e.g., Kennedy et al., (2002), Sherbrooke (1992) and Gross et al., (1998). However, most of the research studies focus on inventory cost minimisation either under finite or under unlimited repair capacity. Some examples are discussed in the following. Diaz et al., (1997) developed a spare part model with limited repair capacity. They approximated the mean and variance of the number of items both in queue and in repair based on queuing theory. Unfortunately, their model was limited only to single echelon repair structure. Sleptchencko et al. (2002) proposed a multi-class multi-server queuing model for a given repair capacity. Zijm et al. (2003) presented a model that determines spare allocation for two-indenture system at one single site with finite repair capacity.

On the other hand, the level of repair analysis LORA which is used to determine the cost-effective repair/discard and repair location decisions has been recognized as a perquisite step in maintenance optimisation. To describe the LORA process for multi-echelon repair structure, integer programming models have been proposed in the literature. For instance, Barros (1998) proposed a multi-echelon, multi-indenture LORA model in which repair decisions are identical to each repair shop. Further, she supposed that all parts at the same indenture-level share the same repair resources and those resources are unlimited. Therefore there is no lead time waiting for repair and the repair resources can be either zero or one at each echelon. Saranga et al., (2006) analysed LORA problem based on the same hypothesis, but they assumed that each part has its own repair resource. Besides, they used Evolver, a Genetic-Algorithms software, to minimise the LORA costs. Finally, Basten et al. (2009) employed a LORA model based on the two abovementioned approaches by relaxing assumptions on repair resource allocation.

Although both LORA and inventory optimisation have been treated extensively, their joint optimisation has not been well examined. In reality, when repair tasks are carried out, spare parts should be available in harmony with discard/repair decisions. Therefore, a spare part inventory strategy based on LORA analysis becomes a crucial issue for maintenance efficiency. The models developed in this chapter determine a joint repair and spare part inventory strategy for complex petroleum equipment. Their main focus is the joint repair and spare part optimisation problem in a setting of restricted M/G/K queueing theory.

8.2 MODEL DESCRIPTION

The model developed in this chapter is a combination of LORA model and VARI-METRIC model to optimise the system availability so that the incurring support costs are less than a predefined threshold budget. The repair structure is defined as a multi-level arborescent configuration in which a limited repair capacity is installed (Figure 8.1). The objective of the model is to decide for a given system:

- Upon failure, which item to repair and which to discard,
- Where are repair/discard tasks located within the repair structure,
- How much investment is needed for repair and spare part inventory throughout the repair structure?

An expected operational availability is achieved against the lowest whole life cost. The decision variables are the spare parts inventory level S and the number of repair servers at each repair level. Therefore, the expected costs include the holding spare parts cost and depreciation costs of repair capacity.

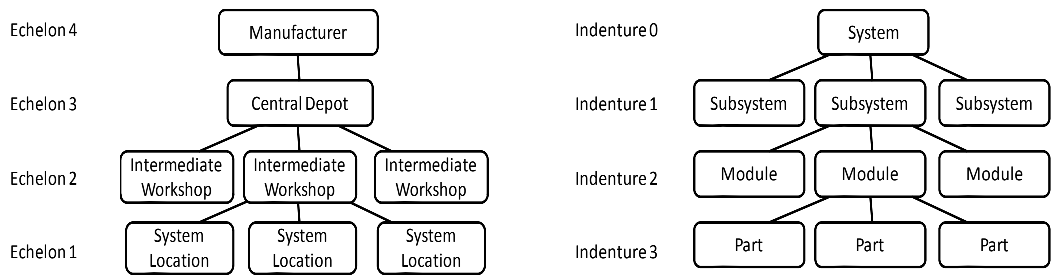

Fig. (8.1): A multi-echelon repair network and a multi-indenture system

The following additional notation is used:

- Servers: the number of repair per repair shop at level j,
- Repair cost (i,j) = the price of repair actions for item i at location j given the number of installed servers,
- the repair shop utilisation rate r(j) is the quotient of the arrival rate and the repair shop service rate,
- costs of spare parts and repair capacity,
- $BO_{ij}(S, Servers)$: the number of backorders (unsatisfied demand) for item i at location j.

8.2.1 THE WHOLE LIFE COST FUNCTIONS

In the model considered, the maintenance costs associated repair shops are influenced by both the installed repair capacity and the quantity of spare part. These costs are represented by LORA costs and inventory cost. Let us begin by expressing the maintenance costs over the system life span. This is given in the following equations.

$$NPV_{LORA} = \sum_{i}^{Item}\sum_{e}^{echelon}(FC_{repair} + \sum_{k=1}^{N}\frac{\lambda_i * VC_{repair}}{(1+r)^k}) * X_{r,e,i} + \sum_{i}^{Item}\sum_{e}^{echelon}(FC_{discard} + \sum_{k=1}^{N}\frac{\lambda_i * VC_{discard}}{(1+r)^k}) * X_{d,e,i} + \sum_{i}^{Item}\sum_{e}^{echelon}(FC_{move} + \sum_{k=1}^{N}\frac{\lambda_i * VC_{move}}{(1+r)^k}) * X_{d,e,i}$$

Where:

λ_{repair}, $\lambda_{discard}$ and λ_{move} denote the annual demand for repair, discard and move respectively.

$$X_{r,e,i} = \begin{cases} 1 & \text{if repair option r at echelon e is selected for part i} \\ 0, & \text{otherwise} \end{cases}$$ the LORA decision variables.

It is worth mentioning that spare part level is optimised under the METRIC-like models in annual life time. In this case, LORA cost used in the joint optimisation is the annual uniform equivalent cost calculated by the following formula:

$$\mathrm{LORA_{cost}} = \frac{\mathrm{NPV_{cost}}}{\sum_{k=1}^{\text{system lifespan}} \frac{1}{(1+i)^k}}$$

Next, LORA cost is split into three subgroups: variable cost, fixed repair cost and fixed spare part cost. Therefore, it cost can be written as follow:

$$\mathrm{LORA_{cost}} = \sum_{i}^{N}\sum_{e}^{echelon}\sum_{r=1}^{3} \mathrm{Vc_{r,e,i}} * \lambda_i * \mathrm{X_{r,e,i}} + \sum_{e}^{echelon} \mathrm{Fc_e} * \mathrm{Y_e} + \sum_{i=1}^{N} c_i \sum_{e}^{echelon} \mathrm{S_{ie}}$$

The total investment in spare parts is given as: $\sum_{i=1}^{N} c_i \sum_{j=1}^{echelon} S_{ij}$

The total investment in repair capacity is given as: $\sum_{i}^{N}\sum_{e}^{echelon}\sum_{r=1}^{3} Vc_{r,e,i} * \lambda_i * X_{r,e,i} + \sum_{e}^{echelon} Fc_e * Y_e$

Where : Y_e denotes the number of repair servers to be installed.

The analysis of this cost function reveals that LORA cost is linear with respect to all decision variables. Besides, and more importantly, this cost function is split into one cost term per decision variable.

8.2.2 PROBLEM FORMULATION OF LORA- INVENTORY JOINT OPTIMISATION

The objective of the Joint LORA and Inventory optimisation is to minimise the number of backorders subject to operation budget. The model is mathematically formulated as follows:

$$\begin{cases} \min \sum_{i=1}^{ech(N)} \sum_{j=1}^{ind(1)} BO_{ij}\left(S_{ij}, Servers_j\right) \\ \text{Subjet to} \\ S_{ij} \geq 0 \text{ and integer} \\ Servers_j \geq 0 \text{ and integer} \\ \sum_i^N \sum_e^{echelon} \sum_{r=1}^3 Vc_{r,e,i} * \lambda_i * X_{r,e,i} + \sum_e^{echelon} Fc_e * Y_e + \sum_{i=1}^N c_i \sum_e^{echelon} S_{ie} \leq Budget \end{cases}$$

This joint optimisation strategy is described by the pair S and Servers. When the item fails, it is replaced immediately by ready-for-use one if it is available or when it is obtained; otherwise it is sent to repair. Combining these terms, the expected downtime includes the replacement time and repair time. The above model is aimed at finding a feasible (S, Servers) pairs that result in the lowest cost for a given system operation level. Alike VARI-METRIC procedure, the optimal (S, Servers) pairs will be obtained by using a greedy heuristic optimisation with a maximum increase in system availability per invested dollar in either spare part or repair capacity is achieved.

The major LORA output that can be fit to VARI-METRIC Procedure is the probability to repair a failed component at a certain echelon. Since LORA decision variables are repair, move, or discard failed item, the repair probability in this model is assumed to be: 1 for discard decision, 0.2 for move decision, and finally 0.8 for repair decision. This choice is underpinned by the fact that in VARI-METRIC model the expected number of pipelines is computed by the following formula:

$$E[p_i] = \lambda_i * (r_i * t_i + (1 - r_i) * O_i)$$

Where : λ_i : failure arte

r_i: the repair probability

t_i: the repair mean time

$1 - r_i$: the probability to move to the next higher repair level

O_i: the mean transportation time.

The three LORA decisions can be analysed as follow:

- When a discard decision is selected at a certain level, there is no move to the next higher echelon. Therefore, the tem $1 - r_i$should be null. That is, $r_i = 1$. Besides, the repair cost is set to a high value to make stock level increase cost-effective than repair capacity increase.
- When a repair decision is selected at a certain level, the repair probability is set to 0.8.
- When a move decision is selected at a certain level, the repair probability is set to equal to 0.2.

The other LORA data that is crucial for spare part and repair capacity trade-off is the price of repair servers known as support test equipment. Their prices are very important compared to the cost of system components. However since they are long term investment their unit cost per repair task can be less expensive than the cheapest item. As a result, a repair step ε is introduced to measure the increase in repair capacity. The model chooses for each iteration between increasing stock level by 1 and repair capacity by ε.

8.3 THE NEED FOR JOINT OPTIMISATION

The adopted marginal analysis is an iterative process initiated by starting settings for the decision variables S and Servers. For each iteration, these variables are increased individually and the increase leading to the biggest proportion of the backorder decrease and the cost increase is selected. The key prerequisite of this process is the decrease of backorders with respect to the decision variables. Therefore, it is useful to see the objective function behaviour when increasing a server vs. increasing spare part inventory during the optimisation. Let us consider the following two cases (1) optimising system availability for a given repair capacity and (2) optimising system availability for given spare part stocks. In the first case servers are set equal to 1 with repair service rate (0.7, 0.8, 0.9, and 0.95). In the second one, all stock levels are set equal to 1 with repair service rate equals to: 0.7, 0.8, 0.9, and 0.95.

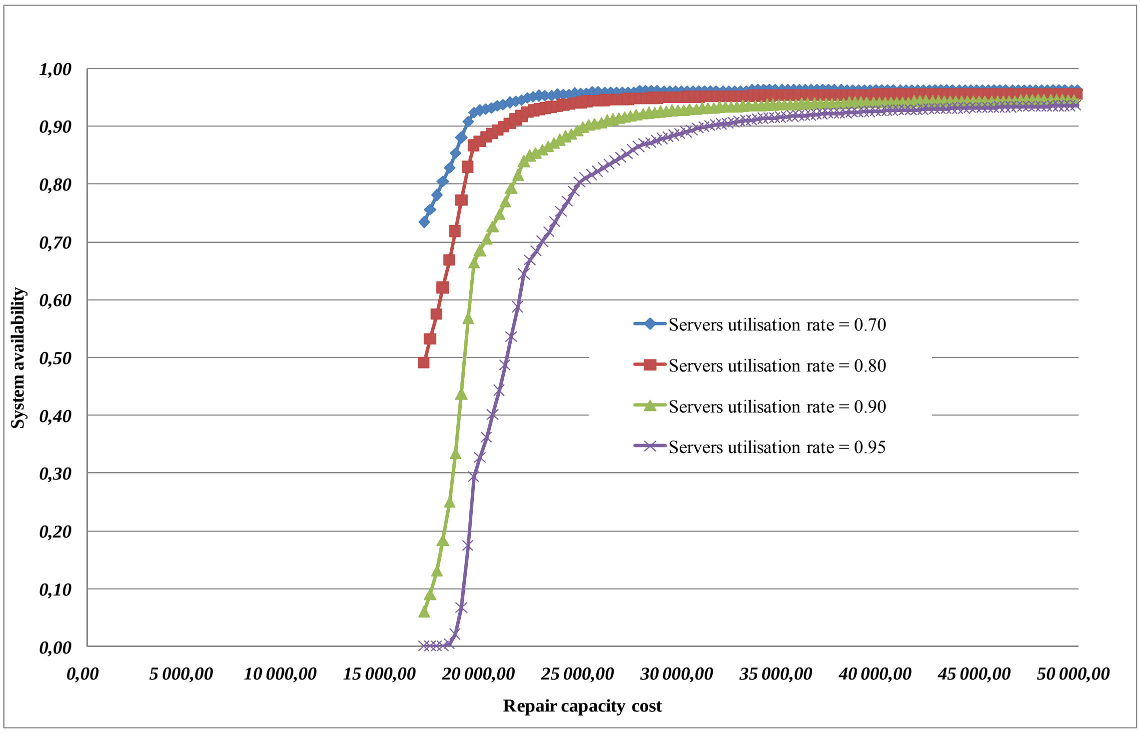

Fig. (8.2): System availability as function of repair capacity

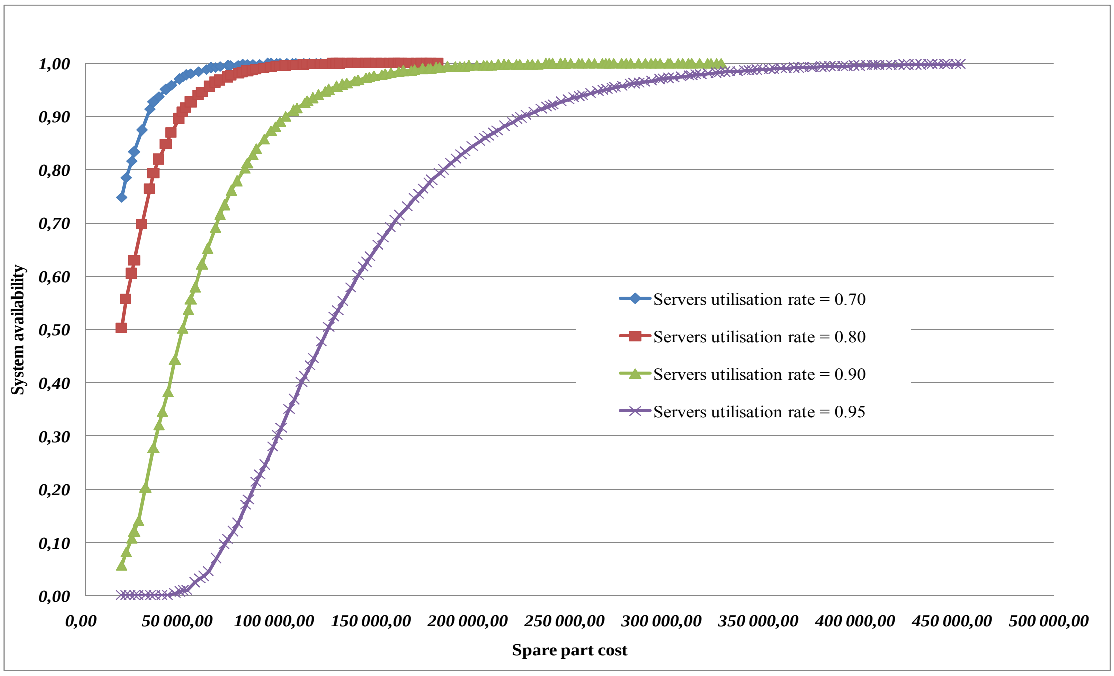

Fig. (8.3): System availability as function of stock levels

Figures 8.2 and 8.3 show the increase of the system availability when increasing either servers or inventory level. It is clear that in these cases, the investment in repair capacity gives the largest contribution to the system availability. Note that the system availability starts at cost level of 20 000 in both cases. However, in the second case the system availability will be greater than 90% when investment cost reach the value of 30 000 with the service utilisation rate equals to 0.95. It is important to mention that to achieve the same level in availability by using only spare part at repair utilisation rate of 0.95, six to seven times in spare part are invested rather than in repair capacity. This example reflects the strategy of low cost of repairing items instead of procuring new ones.

In addition to the above analysis, if repair utilisation rate is less than 0.80, both cases have the same performance. Clearly, depending on the marginal analysis, it is preferable to increase either spare parts or servers. Moreover, it is clear that if a spare part is seen as costly as a repair action, investing in inventory will always be chosen, since the latter will offer quick item replacements and therefore less downtime. However, this is an extreme case and in practice procuring items is more expensive than repair actions. Based on these comments according to the inventory/repair trade-off, a good overall maintenance support solution should be set with respect to both inventory and repair aspects. It is important that inventory optimisation should be considered during repair optimisation and vice versa in order to improve the overall support performance.

8.4 ALGORITHM FOR JOINT OPTIMISATION

Based on the model described in the preceding section, three strategies are carried out to solve the Joint-optimisation LORA and inventory problem, namely sequential, iterative, and integrated optimisation (Figure 8.4).

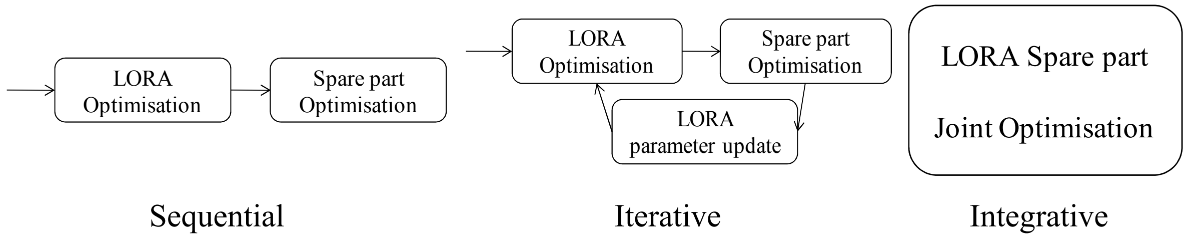

Fig. (8.4): Algorithm for joint optimisation

8.4.1 SEQUENTIAL OPTIMISATION

A sequential optimisation approach is applied to solve joint-problem sequentially through a set of sub-problems where the optimal solution of one problem will be the input for the other one. This approach suffers from some limitations. Firstly, the resulted sub-problems cannot be optimised until the previous one (ones) has been solved. Secondly, the sequential optimisation approach does not consider the interaction impact between different sub-problems. Thirdly, the convergence properties are analysed individually for each sub-problem. Finally, the sequential solution may differ from the optimal solution. However, its simplicity in providing near optimal solutions has given more attention to this approach in practice. Especially for techniques made up of several interactive approaches such as the integrated logistics support ILS.

8.4.2 ITERATIVE OPTIMISATION

The iterative optimisation approach is a decoupled, sequential single-loop approach. As shown in figure 8.5, this approach improves the computational efficiency through parameter update loop. For each iteration, the procedure contains two separate optimisation parts. LORA is firstly formulated by including estimated input parameters then it is refined upon repair decisions from the previous iteration outcomes. The spare part optimisation is carried out iteratively with respect to LORA outputs. The process will stop after verifying the convergence criterion, i.e., no changes to LORA outputs; otherwise the cycle will be repeated.

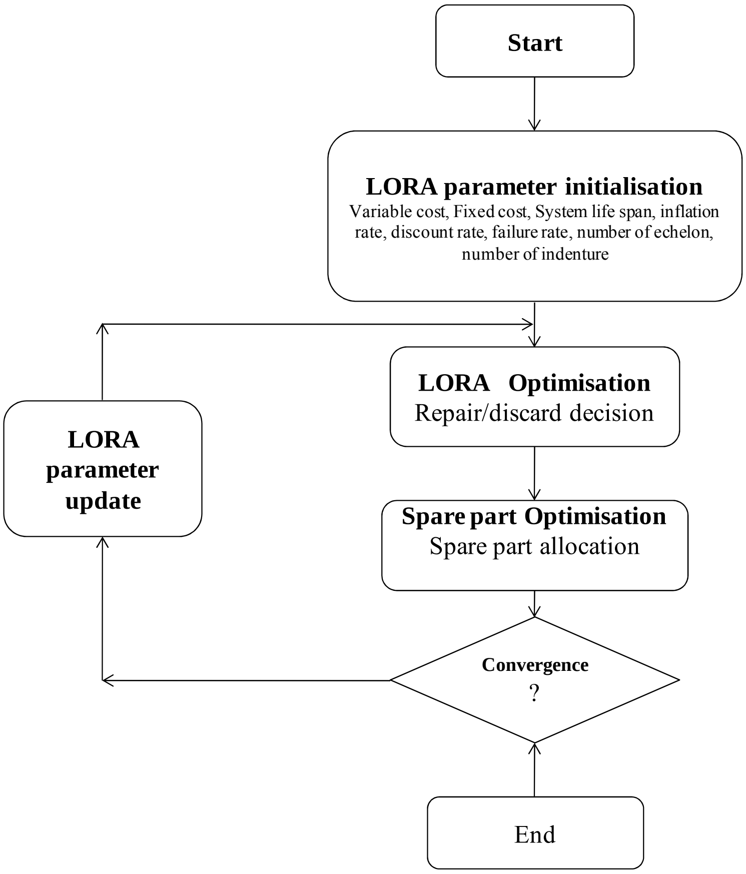

Fig. (8.5): Flowchart of the iterative optimisation

The key idea is that we started the first iteration without considering the cost term related to spare part inventory cost. At this stage, the solution of LORA model will be used in the optimisation of spare part inventory. The new stock allocation, which is minimised with respect to system availability, will be updated by LORA cost function. As a result, the new LORA outcome which is repair/discard decisions will be again identified according to the quantity of spares stored at each repair shop. By executing this process a couple of iterations, spare parts inventory costs for LORA decisions is expected to converge to the optimal solution.

8.4.3 INTEGRATIVE OPTIMISATION

The jointly optimal repair (capacity, inventory) pairs can be calculated for a given problem by using the model provided in section 8.3. The iterative technique generates only one solution from LORA analysis which in turn is used as an input to the inventory optimisation. However, integrated optimisation uses a Genetic Algorithm (GA) to determine a set of best repair/spare part solutions. These solutions require finding the quantities of spare parts at different repair locations and determining the repair capacities of those locations that fulfil operation condition under budget constraint. The difficulty of this joint optimisation lies in the fact that optimising spare inventories and repair capacities which are strongly tied, and separating them into two sub-problems may not lead to the optimal solution.

The starting solutions can be obtained by the sequential optimisation, regardless of whether the inventory costs appearing in the two optimisation sub-problems are the same. The integrative optimisation approach then goes on to improve the quality of the starting solution using neighbourhood and Tabu-Serach algorithm presented in chapter 6. Besides, the integrative optimisation approach generates randomly other solution in order to explore the maximum of solutions. A memory list is used as a best-in-worst-out queue. The worst solutions in the list are removed and replaced by new solutions generated randomly or by genetic algorithm operators (crossover and mutation). The genetic algorithm based optimisation always keeps in the list, among all the generated solutions, the ones that yield the largest performance improvement. Consequently, the overall LORA/spare part inventory solutions improve as the number of iterations increases. The convergence is reached until no new best solution can be found over a predefined maximum number of iterations (1000 iterations in this study).

8.5 NUMERICAL EXPERIMENTS

In this section, a numerical experiment based on gas turbine systems data from chapters 6 and 7 is carried out. It considers six experimental parameters: indenture level, echelon level, repair shop utilisation rate, and repair and spare part costs. Firstly, simulations on a small set of data are conducted to compare the performances of the different optimisation techniques. It is assumed that all system components belong to the first indenture and repaired on first come first served FCFS basis. The objective of this example is to determine the spare parts and required repair capacity mix of a physical system with lifespan of 25 years. The input variables are represented in Table 8.1 to allow comparison with different optimisation methods.

Table (8.1): Optimisation input variables for the example

Input variable	Value
Number of items per indenture	06
Failure rate (failure per year)	Range : 0.11 – 0.22
Supplier procurement time (year)	0.23
Echelon transportation time (year)	0.08
Repair cost for local repair shop	30
Repair cost for central depot	15
Item cost	Range : 300 – 478

Further, the repair utilisation rates for each shop vary from 0.70 to 0.95. That is, the repair mean times are calculated according to these utilisation rates.

Table 8.2 shows the fixed and variable cost comparison for 16 combinations of system availability and repair shop utilisation rate. The columns show the results of integrative & iterative optimisation, compared with sequential optimisation. These calculations were carried out using the Matlab software package.

In order to make a rational comparison, the same set of problem parameter values are used for all optimisation techniques. The results in Table 8.2 suggest that in all cases the iterative and integrative optimisation outperform the sequential optimisation. Fixed cost reductions for a given availability value may be attained when using iterative or integrative optimisation 10% and 21%, respectively. The average improvement (summing fixed and variable costs) over sequential optimisation for the 16 problem instances is 18% and 30%. These results reveal that there is economic benefit to optimising simultaneously these two maintenance support elements: spare part inventory and repair capacity.

Table (8.2): Optimisation technique comparison

Availability threshold	Server utilisation rate	Iterative vs. sequential optimisation		Integrative vs. sequential optimisation		Integrative vs. Iterative optimisation	
		Δ fixed cost	Δ variable cost	Δ fixed cost	Δ variable cost	Δ fixed cost	Δ variable cost
0.86	0.70	-2.83%	-4.12%	-4.69%	-12.16%	-1.92%	-8.45%
	0.80	-4.66%	-7.95%	-8.91%	-17.28%	-4.51%	-10.32%
	0.90	-5.80%	-13.15%	-7.72%	-21.91%	-2.07%	-10.39%
	0.95	-8.22%	-19.27%	-13.11%	-28.86%	-5.42%	-12.48%
0.90	0.70	-2.91%	-4.6%	-5.70%	-9.53%	-2.89%	-5.23%
	0.80	-5.56%	-9.9%	-10.09%	-15.76%	-4.86%	-6.62%
	0.90	-7.91%	-18.4%	-17.19%	-19.24%	-10.26%	-1.02%
	0.95	-8.60%	-26.3%	-20.97%	-30.95%	-13.79%	-6.83%
0.95	0.70	-3.23%	-4.1%	-5.99%	-8.44%	-2.87%	-4.57%
	0.80	-7.06%	-9.3%	-11.72%	-14.06%	-5.09%	-5.40%
	0.90	-8.26%	-15.8%	-14.09%	-18.23%	-6.47%	-2.97%
	0.95	-8.55%	-18.9%	-17.40%	-27.97%	-9.86%	-11.78%
0.99	0.70	-3.27%	-2.6%	-3.89%	-6.09%	-0.65%	-3.60%
	0.80	-8.00%	-6.7%	-14.22%	-16.03%	-6.88%	-10.18%
	0.90	-9.53%	-11.8%	-12.57%	-20.81%	-3.44%	-10.53%
	0.95	-9.84%	-17.2%	-12.44%	-26.51%	-2.95%	-11.72%

Even though the cost reduction values may differ between iterative and integrative optimisation, the computational time may have a great impact on the performance of these optimisation techniques. The next step was intended firstly to investigate this aspect over a variety of problem instance, and to attempt to find out when the time divergence may become large. The experiments chosen related to single-echelon, two-echelon repair network structure; one, two and three indenture system are chosen. The number of system components was 6 for the first-indenture, 23 for the second-indenture and 53 for the third indenture. For all cases the other data input varied as follows: system availability = {0.86, 0.90, 0.95, 0.99} and repair utilisation rate = {0.70, 0.80, 0.90, 0.95}. In total this gave 96 different problem instances.

Table (8.3): Optimisation computational time (seconds)

Availability threshold	Server utilisation rate	Repair echelon	Single-indenture system			Two-indenture system			Three-indenture system		
			Iterative optimisat.	Integrative optimisat.	Δ	Iterative optimisat.	Integrative optimisat.	Δ	Iterative optimisat.	Integrative optimisat.	Δ
0.86	0.70	1	11	31	20	175	493	318	995	1213	218
		2	18	38	20	214	452	238	902	1385	483
	0.80	1	11	26	15	120	285	165	943	1239	296
		2	21	59	38	325	914	589	929	1207	278
	0.90	1	13	31	18	173	414	241	952	1672	720
		2	23	46	23	203	407	204	1117	1644	527
	0.95	1	15	31	16	179	371	192	1373	1846	473
		2	23	63	40	357	979	622	1240	1860	620
0.90	0.70	1	14	37	23	113	300	187	1249	1516	267
		2	24	52	28	360	780	420	1514	1449	-65
	0.80	1	16	48	32	201	604	403	1096	1399	303
		2	26	84	58	384	1242	858	1169	1450	281
	0.90	1	17	49	32	171	493	322	1263	1483	220
		2	30	87	57	323	939	616	1125	1677	552
	0.95	1	15	56	41	165	618	453	1135	1551	416
		2	33	100	67	295	895	600	1278	1913	635
0.95	0.70	1	25	66	41	391	1033	642	1745	2095	350
		2	27	88	61	407	1327	920	1990	2029	39
	0.80	1	17	56	39	250	826	576	2051	2234	183
		2	50	100	50	509	1018	509	2256	2313	57
	0.90	1	22	79	57	215	772	557	2307	2489	182
		2	46	128	82	633	1762	1129	2199	2598	399
	0.95	1	24	80	56	216	720	504	2519	2798	279
		2	59	190	131	936	1316	380	2668	2885	217
0.99	0.70	1	27	80	53	306	909	603	1735	2127	392
		2	28	89	61	264	839	575	1761	2597	836
	0.80	1	28	61	33	265	578	313	1932	2795	863
		2	56	133	77	783	1859	1076	2056	2840	784
	0.90	1	41	94	53	524	1202	678	2163	2910	747
		2	74	153	79	1013	2096	1083	2128	3004	876
	0.95	1	32	88	56	371	1020	649	2359	2954	595
		2	100	199	99	1062	2113	1051	2800	3112	312

In Table 8.3, the computational times for integrative versus iterative optimisation are summarised. As expected, the iterative optimisation gives less computational time than the integrative optimisation. On average the difference was 357 seconds, but it varied dependably on the cases. The largest difference was 1129 seconds, but only one had a negative difference of – 65. The computational time for the two optimisation techniques has increased dramatically when the number of items increases. However, this joint optimisation is a tactical maintenance decision that is conducted only once or twice a year so that computation times could be less relevant. Still, these techniques may cause practical problems for systems containing thousands of parts.

8.6 COMPUTATIONAL RESULTS FOR JOINT OPTIMISATION INVENTORY AND REPAIR CAPACITY ALLOCATION

This section presents the computational results for inventory and repair capacity allocation discussed previously. In order to gain a deeper understanding of maintenance support optimisation, two different instances are considered. Firstly, the system availability is computed as a function of inventory cost for a given capacity, termed 'option A'. Then, the system availability is computed where inventory cost and repair cost are the two variables to be minimised, termed ‘option B’. Besides, the analysis given below is based on the operation requirement in which system availability should always be kept greater than 86%.

In order to determine which inventory-repair allocation would help in minimising the maintenance support cost across the entire multi-echelon network, the two instances, each including several scenarios, are solved to optimality. The repair capacity which is represented by the number of repair servers is considered as ample capacity when the repair shop utilization rate is less than 70%. With respect to these settings, the contribution of the joint optimisation will be trivial. However, the repair capacity is denoted as a tight capacity when this rate is greater than 70% and joint optimisation will trade-off any invested dollar between repair capacity and spare parts.

Figures 8.6 and 8.7 depict the system availability values of the two instances option A and option B; the repair shop utilisation rate increases from 0.7 to 0.95. The following observations can be drawn from these figures.

- The main difference between the two options is that the numbers of items that can be repaired simultaneously in repair lines are greater in option B than those in option A. The queue time in option B is lower and therefore less repair time is needed.

- Different rates of repair shop are simulated to find out how the system availability is affected by rate and how much to invest in repair capacity to satisfy the operation requirement. It is found that, if the repair shop utilisation rate is small enough to prevent a queue of items waiting for repair lines; the system availability will be satisfied at low support costs (1000 and 950 for the options A and B respectively). Maximum system availability is therefore ensured with the low repair shop utilisation rate. Nevertheless, this policy is at the expense of possessing vacant repair capacity for a prompt response to repair workloads.

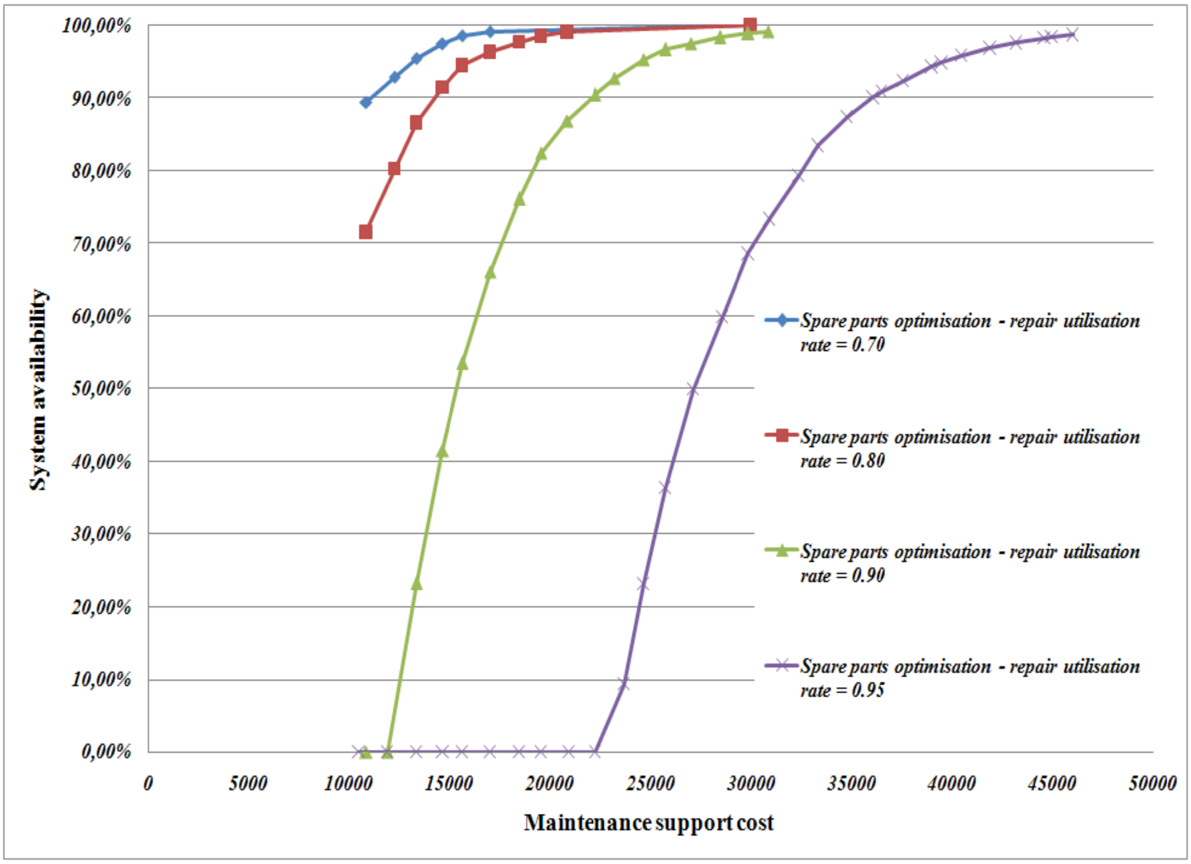

Fig. (8.6): Spare part optimisation

- In addition, investing in repair capacity yields cost-effective solutions for operation requirements. When support cost is at 15000, system availability is at its maximum value for all scenarios for option B and only when the utilisation rate is less than 0.80 for option A.

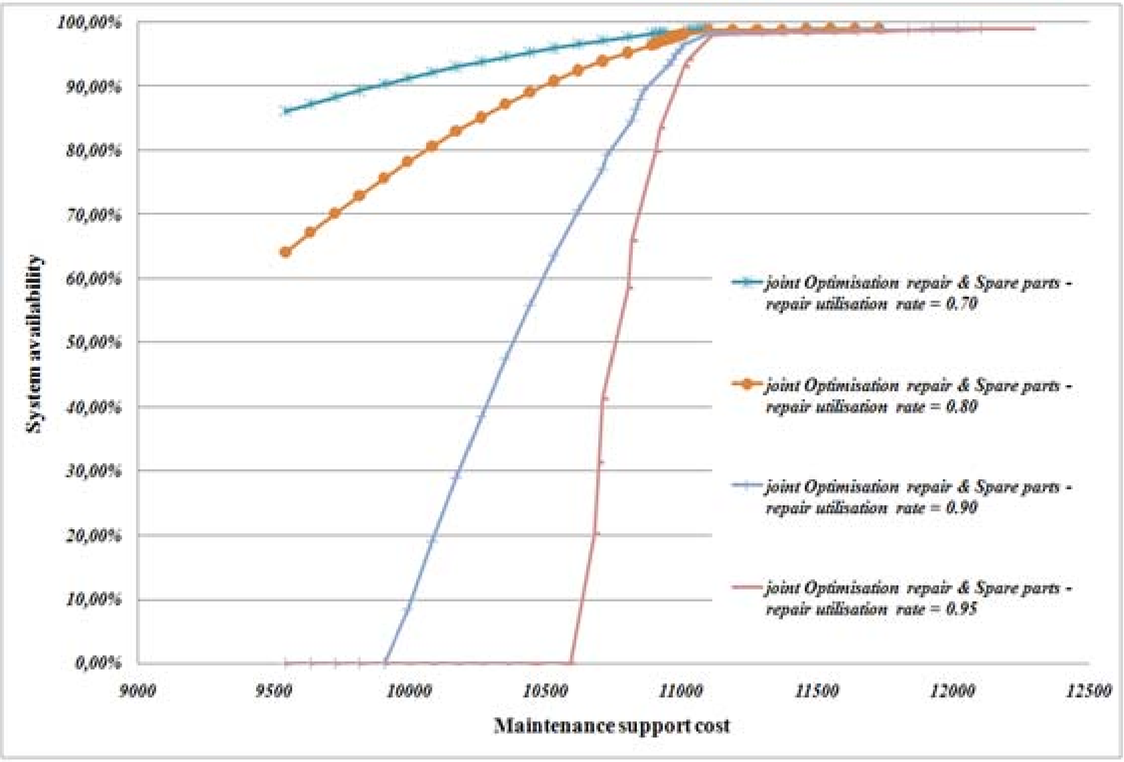

Fig. (8.7): Spare part optimisation

- A thorough investigation of the results of the two options as shown in figure 8.8 reveals that option B have a clear advantage over option A. Therefore, option A can be excluded. As expected, the inventory cost for the same system availability value is greater in spare part optimisation (option A) than that found in joint optimisation option B. However, this depends strongly on the price ratio of repair servers to component procurement. It has been found that the number of required spare part has dropped drastically by integrative repair capacity tradeoffs, as shown in table 8.4. The number of spare parts seems to decrease with higher repair servers since their increase means a short repair time and as a result less spares are needed.

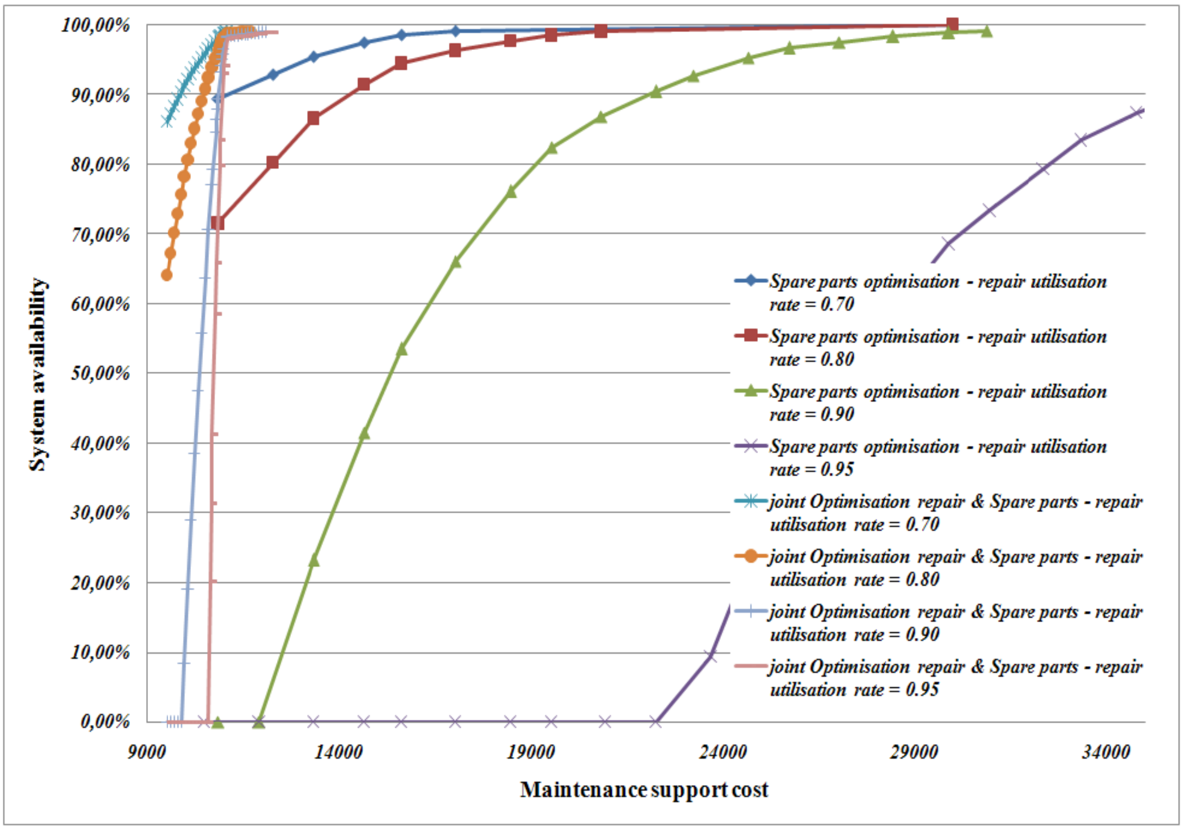

Fig. (8.8): Spare part optimisation

Table (8.4): Spare allocation throughout the repair shops

	Joint Optimisation				Spare part Optimisation			
Location	base	local shop 1	Local shop 2	Local shop 3	base	Local shop 1	local shop 2	local shop 3
Item 1	1	3	3	3	1	15	15	15
Item 2	1	3	3	3	1	11	11	11
Item 3	1	3	3	3	1	9	9	9
Item 4	1	3	3	3	2	11	11	11
Item 5	1	3	3	3	2	13	13	13
Item 6	1	1	1	1	2	10	10	10
servers	4	5	5	5	1	1	1	1

8.7 SUMMARY

In this chapter, a multi-echelon multi-indenture system has been considered for which LORA and spare part stocking decisions need to be made so as to satisfy the operation service level at the lowest whole life costs. Especially, it discussed the joint allocation of repair capacity and spare parts problem. The joint optimisation methodology was developed based on three techniques: sequential, iterative and integrative optimisation. This techniques tried to identify the best spare part and repair capacity mix for a given system availability threshold. The results obtained for different repair structures have showed that integrative optimisation can be valuable. It yielded to an average improvement of 13% over the best form of iterative optimisation. More importantly for over 16 of the cases examined, the difference was more often greater than 10%. However, iterative technique is likely to deliver satisfactory results equivalent to integrative optimisation and it can be the preferable technique for its low computational time. Another important remark is that sequential optimisation, traditionally adopted in practice, can be bad since there are no loops for further result refinements.

Another advantage of this joint optimisation is that a set of optimal mix between maintenance support resources is found gaining insight in the relation between the whole life costs and the operational availability. It has been found that the optimal mix is very sensitive the utilisation of repair shops. The latter which varies in practice between 0.8 and 0.95 influences significantly the balance between the number of servers and the spare part levels.

CHAPTER 9 MODEL TESTING AND VALIDATION

9.1 INTRODUCTION

This chapter presents the framework and results of validation studies that have been performed on the maintenance support model are reported. In accordance to the research methods process presented in chapter 5, the developed maintenance support model has been tested and validated with two phases. The first phase was a theoretical analysis where the model was tested using a set of similar case studies given in the literature. In a second phase, the model has been presented to a panel of experts for further refinements. The aim of this phase was to provide examples with realistic data to emphasise the benefits of the model and could be used for stimulating discussions of the expert panel. This process is depicted in figure (9.1) and different validation phases are reported in detail in the following sections.

This chapter is organised as follows: initially the design of validation instrument was discussed. Then, the first validation approach based on the theoretical analysis is given. After that the panel validation is presented. Finally, a general evaluation of the model is presented.

9.2 DESIGN OF VALIDATION INSTRUMENT

This validation study represents the final step of the model development. In previous chapters the rationale for this model is provided and how the different support elements have been integrated to enhance best practices to maintenance strategies. A primary objective of this model is to optimise whole life support cost related to maintenance with respect to operation requirements. To ascertain to what extent the developed model achieved its objectives, a validation instrument based on detailed comparison with case studies in similar field and on expert panel feedback was carried out. The figure 9.1 presents the combination of theoretical analysis and expert validation to test the interface of the framework. Firstly, the model was used in re-assessing case studies considered in similar research works. Since the model is a joint optimisation of two integrated logistics support elements namely LORA and spare part inventory, it is meaningful to test model efficacy against preselected research works treated by either LORA or spare part inventory. Testing with known cases and with prior outcomes allow a twofold improvements: (1) how accuracy the developed model can handle different support elements individually and (2) what are the pros and cons of their integration. Secondly, the expert validation was used to improve and test the model interface. The expert panel has mainly given insight on topics including interface design, interface simplicity and ease of use of the model.

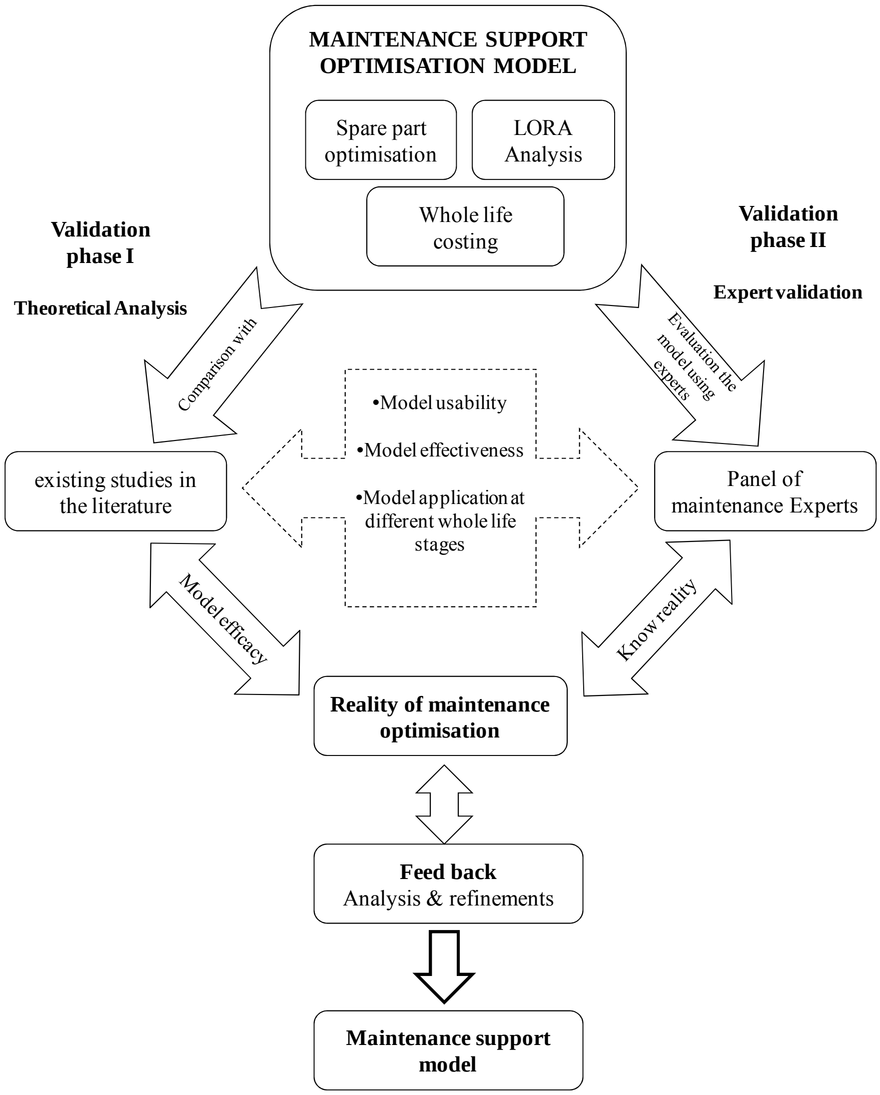

Figure 9.1: The Process for model interface testing and validation

It is often good to test any developed system against an independent panel of experts. Since the development of models for complex issues can go beyond the capability of single person, the use of expert opinion is inevitable (Boland et al., 1992 and Brehmer, 1991). The efficacy of this method relies on addressing the following two problems. Firstly, the selected of the panel of experts needed for such an evaluation should be familiar with maintenance repair design and monitoring. In addition, the experts should also be selected based on their experience and knowledge in maintenance field. This exploratory study is intended to find out the strengths and weaknesses of our model based on the opinion of a panel of experts.

9.3 THEORETICAL VALIDATION

This section presents a simulation of additional repair examples using various algorithms developed in chapters 6 to 8 and their comparison to existing research works. This is done to validate the developed model and to highlight some of its features. The first stage of this testing approach requires that different sub-models that constitute the maintenance support model operate efficiently when considered separately. Both spare part inventory control and LORA analysis have rigorously been tested to ensure their ability to estimate maintenance support costs for a wide range of repair structures with regard to operation conditions.

- **CASE STUDY**

In this example, the multi-echelon multi-indenture algorithm was used to solve a simple example problem given in Rustenburg et al., (2001). In this example, it is required to estimate spare part inventory budget for a given availability threshold for a fire extinguishing system. This system consists of two main parts (a pump and an electromotor). The pump has three subassemblies (Bearing, seal and casing) and the electromotor has two subassemblies (Rotor and stator).

Table 9.1 : Input data (Rustenburg et al., 2001).

		λ (failure/year)	repair time at local bases (year)	repair time at central base (year)	repair probability at local bases	transportation time (year)	Cost
Part 1	Pump	19	0.03	0.1	0.2	0.2	19800
Part 2	Electromotor	15	0.03	0.1	0.2	0.2	50800
Part 3	Bearing		0.1	0.3	0.2	0.2	3300
Part 4	Seal		0.1	0.3	0.2	0.2	4500
Part 5	Casing		0.1	0.3	0.2	0.2	4400
Part 6	Rotor		0.1	0.3	0.2	0.2	1500
Part 7	Stator		0.1	0.3	0.2	0.2	4500

Commonality matrix

	Part 3	Part 4	Part 5	Part 6	Part 7
Part 1	0.32	0.47	0.21	0	0
Part 2	0	0	0	0.29	0.71

As it has been done in Rustenburg work, the model has been run for a large budget constraint and all pairs of stock allocations and their related system availability are shown in table 9.2.

Analysing table 9.2, the model outcome and Rustenburg results are slightly different. For the same inventory investment, the maximum absolute difference in availability does not exceed 1.50%. On the other hand, the maximum difference in inventory investment for a given availability is around 400.000. The calculated number of spare parts at the same availability level (74.84%) is identical to those obtained by Rustenburg work.

Table 9.2 : Base stock levels of example (9.1).

	Rustenburg work Availability: 74.84% Investment: 2302100		**Model outcome** Availability: 74.84% Investment: 2302100	
	base stock level at local depot	base stock level at local depot	base stock level at local depot	base stock level at local depot
Pump	7	6	9	4
Electromotor	4	4	8	4
Bearing	12	1	10	1
Seal	16	1	15	1
Casing	8	1	7	1
Rotor	12	1	8	1
Stator	21	1	17	1

9.4 EXPERT VALIDATION

The model usability is tested for validation in context of real industrial settings. The objective of using a real industrial testing is not only to demonstrate the usability of the model but also to observe its limitations for further improvements and refinements. In addition, this validation investigation is intended to minimise the gap between the ability of model to deliver cost effective decisions and the industrial need. Therefore, the model is validated for maintenance support optimisation by interviewing petroleum maintenance experts. These experts are familiar with the reality of maintenance support and they are invited accordingly to assess how valuable the model would be in the petroleum organisations. For this purpose, the model developed in chapter 8 was used in re-assessing case study dealing with gas turbine.

During a review of the model and its related data and hypothesis, the panel of experts raised a number of critical questions reorganised as following:

- What are the strengths, merits, limitations, gaps of the proposed model compared to the actual supportability approach?
- By what means could the model be improved, so as to minimise the gaps with practice and maximise the relevance, reliability and utility of model outputs?

9.4.1 PILOT STUDY

A full illustration of the model usability may require a huge effort in gathering input data when maintenance supportability for several installed systems is simulated. It would be very lengthily for this research to attempt to present the model usability for a number of petroleum equipment. This choice is motivated by the fact that data are either missing or incomplete at real-world investigation. Therefore, the model validation has focused on presenting the usefulness and applicability of the model for gas turbines studied in the previous chapters.

In this validation and testing study, two real turbines were used for model illustration. The needed data of these two examples were supplied by some participating experts. Besides, the brands of the turbines and their producers were not revealed in order to ensure the confidentiality issues related to this study. Turbine A and turbine B were used to designate the selected petroleum equipment to undertake the model assessment.

9.4.2 SELECTING PANEL EXPERTS

The skills and experience of experts have a great effect on the validation results (Hvannberg et al., 2007); the more experienced a panellist is, the more pertinent the evaluation outcome is. Requests were sent to many SONATRACH experts who have good knowledge in maintenance area but only twenty five agreed to participate. These experts were nominated to form a "Panel of Experts" based on their expertise in the field of maintenance at national petroleum company SONATRACH as well as number of working years. This panel consisted of three types of experts: three heads of maintenance department, eight procurement engineers and eleven maintenance operators. These professionals were approached firstly at their place of work and secondly through emails. Besides, three lecturers at the Algerian Petroleum Institute considered as academia experts were interviewed on the usefulness and applicability of the model. A written questionnaire (as shown in Appendix A) was used to obtain the experts' judgement. Initial interviews were conducted with each of the panellists to prepare and guide them for the accomplishment of the validation questionnaire.

9.4.3 METHODOLOGY

Validation and test results about the usability of the model were collected on two approaches. First, the panellists ranked the model usability by means of a questionnaire. Then the same panellists were to test the model for qualitative analysis by collecting their comments and suggestions. Besides, an analysis of variance was carried out to detect any possible differences in expert assessment. The surveys study was structured around six phases:

1. Definition of the underlying theory and the model structure
2. Definition of the pilot study
3. Expert panel initialisation and discussions
4. Questionnaire building
5. Validation construction process
6. Validation result processing.

During the third phase, the initialisation and discussions were carried out with a reviewing panel of SONATRACH to come up with initial success criteria for model implementation. Firstly, emails were sent to the panellists to invite them to enumerate the measurement criteria that should be considered when validating models related to their field of expertise. Table 9.3 presents the chosen criteria and their frequencies given by the 25 respondents. In this review, usability was most frequently measured, followed by model output and model adaptation.

Table 9.3 : the measurement criterion of the model validation.

N°	Measurement criterion	Frequency over 25
1	Usability	17
2	Model output relevance	11
3	Adaptation	11
4	Simplicity	11
5	User expertise	10
6	User satisfaction	8
7	Input data	8
8	Model interface environment	7

Secondly, another set of criteria was provided to the experts from literature in system usability studies (Nielson, 1993, ISO 9241-11, 1998, Demers et al., 1996) and Shackel, 1991). The above criteria were completed and modified based on expert feedback to reflect the characteristics of maintenance environment. As a result, twenty six questionnaire items were generated in relation to the model validation and testing. These items can be classified under the following groups:

- Variables concerning the model usability: usability is considered by ISO 9241-11 (1998) as the degree to which a system can be used in a specified context to attain particular objectives with efficiency, effectiveness and satisfaction of use. Based on this definition, usability is therefore measured by means of three variables, namely effectiveness, efficiency, and satisfaction. In this validation study, these variables are defined as follow:
    - Efficiency: means the model capacity to generate satisfactory results with a minimum amount of required input data;
    - Effectiveness is the degree to which the model fulfils its intended goals or functions; and
    - Satisfaction reveals level of approval toward using the model.
- Variables concerning the model
    - Sound theory

    - Model structure
    - Model content
    - Simplicity
    - Learnability and ease of use
    - Helpfulness and problem solving capabilities
- Variables concerning the model adaptability
    - User background and experience
    - Familiarity with the theory
    - Required input data
    - Usefulness of output data
    - Missing parameters
    - Applicability at different whole life phases
    - Adaptability to the organisation environment
    - Adaptability to user culture
- Model weaknesses and improvement

The questionnaire was reviewed by academia experts at the Algerian petroleum institute on a variety of aspects including technical, language and item redundancy. The questionnaire measure consists of 26 items clustered into 4 groups, namely model usability (3 items), model (6 items), model adaptability (8 items) and model weakness and improvement (4 items). The respondents graded these items using a 5 Likert-type scale from 1 to 5 where '1' is the lowest and most negative judgement on the scale, '3' is the average judgement, and '5' is the highest and most positive judgement. The selected items are presented in Table 9.4. Fowler (2002) asserted that a Likert scale has the advantage to be easily understood and it well discriminates among respondents views. In addition, it requires short questionnaire items of a few lines. Finally, it is straightforward to analyse and interpret responses and the capability to get summated values.

Table 9.4 : identified success criteria.

Success Criterion	Purpose	Question sample
Usefulness	Effectiveness Efficiency Satisfaction	I am successful in general in finding required data when using the model. Overall, the model is useful in helping me I achieve what I want using the model Can the results obtained by the model be applied?
Adaptability to environments	Satisfaction with the adaptability features of the model to environments	How satisfied are you with the adaptability features of this model to environments?
Adaptability to culture of users	Satisfaction with the adaptability features of the model to the users.	How satisfied are you with the adaptability features of this model?

9.4.4 RESULTS & ANALYSIS OF THE VALIDATION

As mentioned above, the expert validation is based on usability questionnaire designed to assess user satisfaction related to model attributes and model results. For the 26 questions, descriptive statistics were examined including mean, maximum, minimum and standard deviation. Table 3 provides the descriptive statistics for questionnaire responses. In overall, the model was given an average rate of 3.59 with SD = 1.07, which is higher than the score 3.0.

Table 9.5 : Questionnaire results.

		Mean	max	min	SD
1 - Model Usefulness					
Effectiveness					
1	I can estimate required spare part using the model.	3.80	5.00	2.00	0.87
2	I am successful in general in finding required data when using the model.	3.60	5.00	1.00	1.00
3	Overall, the model is useful in helping me	3.68	5.00	2.00	0.75
4	I achieve what I want using the model	3.48	5.00	2.00	0.92
5	The results I obtain from the model are useful.	3.60	5.00	2.00	0.87
6	The model covers topics that I need.	3.32	5.00	2.00	0.85
Efficiency					
1	It is easy to obtain the results that I need	3.56	5.00	1.00	1.39
2	The model is easy to use in general.	3.88	5.00	2.00	1.13
3	I can obtain the results in adequate time using the model	3.12	5.00	2.00	1.01
4	The model is well designed to achieve what I need	3.48	5.00	2.00	1.00
5	Using the model enhances the quality of my work	3.96	5.00	2.00	1.21
Satisfaction					
1	Do the results obtained by the model look logic for me	4.20	5.00	3.00	0.58
2	Can the results obtained by the model be applied	3.28	5.00	2.00	1.21
3	Do the results differ largely from those E138	3.48	5.00	2.00	1.05
4	Does not take a great deal of effort to become familiar with the model	3.52	5.00	2.00	1.16
5	The terminologies used on the model are easily understandable.	3.40	5.00	2.00	1.22
6	Using the model makes it easier to do my work	3.12	5.00	2.00	0.97
7	It was easy to learn to use the model	4.12	5.00	2.00	1.05
8	I feel optimistic that the model will be successful	3.60	5.00	2.00	1.22
2 - Model Adaptability to environments					
1	Required input data are easily obtained from organisation resources and archives	3.84	5.00	2.00	0.85
2	Usefulness of the model output by the organisation	3.56	5.00	2.00	1.00
3	Do missing data at your level could be easily estimated?	3.40	5.00	2.00	0.91
4	Applicability at different whole life phases	3.76	5.00	2.00	0.83
5	How important to you are the benefits provided by to your organisation?	3.72	5.00	2.00	0.98
3 - Model Adaptability to culture of users					
1	Familiarity with the theory	2.12	3.00	1.00	0.60
2	Ease to manipulate the model	3.60	5.00	2.00	1.26
3	It meets my needs.	3.72	5.00	2.00	1.06
4	I quickly became skilful with it.	3.72	5.00	2.00	1.34

When investigating questionnaire items, the assessment showed a range of averages between 4.20 and 2.12. Only two panellists, however, gave an overall score less than 3.0 (which could be considered as 'insufficient') with mean values of 2.96 and 2.9, respectively. This expert survey revealed that the usability and the overall quality of the model were rated as sufficient. The model was valued to offer a more theoretical and valuable methodology to the maintenance-support problems. Panellists also found that they could recommend the use of the model since it links supportability aspects with system availability and readiness.

Table 9.6 : Model satisfaction results.

	Model Usefulness			Model Adaptability to environments	Model Adaptability to culture of users
	Effectiveness	Efficiency	Satisfaction		
Mean	3.58	3.60	3.59	3.66	3.29
max	5	5	5	5	5
min	1	1	2	2	1
SD	0.88	1.18	1.12	0.92	1.28

According to the mean values of each assessment group (Table 9.6), it can be concluded that all experts have high expectations on the model ability of solving problem and its helpfulness. They find it easy to carry out their tasks of using the model. However, the underlying theory seemed to be the least valuated by the participants. The following points summarise the comments that arose from questionnaire answers, and specific suggestions and ideas.

1. At first impression, the model offered a package which could be used for repair location optimisation, spare part optimisation for a given repair configuration and joint optimisation of spare part and repair location. The model encouraged a better integration of procurement teams and maintenance staff.

2. There is a significant difference between the model approach and the actual used support provision method which is based only on manufacturer guidelines and recommendations. The thoroughness in terms of the underlying theory and the inclusion of LORA analysis indicate that the model is different indeed, offering more advantages for decision making.

3. It was also found that the use of LORA analysis in the early stages of system installation might help to achieve cost effective decisions. The need for immediate repair actions is the main target since the Petroleum industry operates in a large environment.

4. A common idea from the questionnaire is that of component criticality analysis. This is identified as a key point when dealing with procuring and storing spare for all petroleum equipment. It was felt that critical-part procurement is prescribed by safety stocks and operation requirement. Certainly, there is a need to demonstrate how the model addresses part criticality within pilot cases. Eleven panellists, who emphasized this issue, found that spare part mix delivered by the model based on system availability is a good way to deal with this problem. Therefore, this would become a strong rationale for the model adoption and use.

5. Input data was regarded as being fundamental to the way in which the system might operate. Those responsible for using the model might have sufficient technical expertise to analyse the data before running the model. This issue may make the model outcome inconclusive if there is some missing data which must be estimated. That is, the input data will be obtained from system historical database and the model should be designed to accommodate this point.

6. There was a comment regarding the description of the team that should use the model, in addition whom might be concerned by taking supportability decisions. Since the model is based on Integrated Logistics Support ILS, different players may be involved in using its output such as maintenance representatives, procurement engineers, operation managers, etc. Phone discussions with the panellist who arose this issue focused on the model usability and the definition of the model users. This point was extended to the other panellists and they felt that the model could be equally useful to all actors involved in procurement and maintenance and it might be a good solution for conflicting issues related to spare part procurement.

7. Finally, there were some comments regarding to the user training on the theoretical background of the model, i.e., level of repair analysis and genetic algorithm optimisation technique. Training of the users in integrated logistics support ILS is considered a necessity by the group of panellists. Some of them have suggested developing a training program on the topic and using the model as part of the training.

9.5 RECOMMENDATIONS FOR FUTURE MODEL EXTENTION

The following suggestions were noted as actions that should be taken into account to help investigate the sustainability of the research.

1. This validation study should encompass more extensive pilot case studies, including other different petroleum systems. This will permit users to find additional comments and suggestions on the usability of the model. Issues related to confidentially and real-world data availability have been the major obstacles toward exploring more situations.

2. It was also agreed that scheduling seminar events over time for SONATRACH engineers to refine the model and enhance its applicability.

3. Experts felt that the main challenge in enhancing the model will be to incorporate other ILS elements such as: reliability centred maintenance RCM. Since this work has covered only a research on ILS by focusing on the joint optimisation spare part provision and level of repair analysis LORA, the plan for a future research work is to cover research in reliability centred maintenance RCM.

4. It was felt that cases studies of different systems sharing the same repair resources could be useful to refine the model.

5. It worth simulating maintenance supportability for new projects prior any system acquisition.

6. The validation study has demonstrated that several refinement of the framework should be done to integrate other ILS elements. However, there is

no comment about the framework interface improvement. This is mainly due to the fact that the interface has been developed in several phases with close consultations of selected framework users.

9.6 SUMMARY

In this chapter, the evaluation of the final product of the research was presented. The model output has been assessed with data from a set of studied taken from the literature and from industrial settings. This chapter summarizes the validation work that has been performed on the model. Such a work encompasses both benchmark studies where the model results are compared to published researched and experiment studies where a set of experts are invited to evaluate the model by simulating a number of maintenance support scenarios.

Numerical simulations in these various situations have shown that the model is able to deliver the optimal spare part provision and the repair locations as well. In accordance with other studies, the model showed effectiveness in predicting cost effective maintenance supports. Besides, the results have shown that maintenance supports are improved by the proposed joint optimisation of these two support elements. The expert validation indicates that even though implementation settings and specifications were only related to the petroleum industry, the surveys and discussions revealed important differences that demonstrate the benefits of the use of LORA and the spare part joint optimisation among all elements of the maintenance support. However, there exist some issues and requirements for further enhancements that are presented in the next chapter.

CHAPTER 10 SUMMARY, CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

10.1 SUMMARY

A key feature of actual petroleum assets is that they have become more complex with little change of the initial design once they are installed. Hence, their performance during operation phase depends mainly on the maintenance and its related activities. A new competitive environment has been initiated by the restructuring of Oil and Gas industry in many countries like Algeria and increasing efficiency requirements have become the first target for asset management. As a result, the Algerian Petroleum company SOANATRACH is attempting to address this issue by looking for optimal long-term results for petroleum equipment through application of adequate methodologies. In particular, the increase in the support and maintenance whole life costs, its asset managers are compelled to optimise availability of the installed systems, while operation budget has to be minimised without jeopardising system outputs. Given that most of the cost decisions related to maintenance and support are established on expert estimations and past experience, a request for a whole life costing WLC technique arises. Moreover, a WLC technique combined with the integrated logistics support approach will present a better way to optimise maintenance decisions. Therefore, the maintenance supportability cost optimisation and the whole life costing WLC were reviewed critically.

10.2 REVIEW OF OBJECTIVES AND MAIN FINDINGS

As discussed in the first chapter, the outline of the objectives was as follow:

10.2.1 REVIEW OF FIRST OBJECTIVE

Undertake an extensive literature review to understand basic ILS requirements and to identify gaps where ILS implementation should be improved.

A review of relevant material in the whole life costing WLC literature was given in chapter 1. The review revealed that WLC has not been well adopted in practice despite its theoretical development. The issue that has emerged to enhance WLC implementation in real-world was the development of a suitable model based on the integrated logistics support ILS. The review showed that maintenance costs of complex systems constitute the bulk of WLC. Therefore there is room for improvement among maintenance optimisation models. In this area of optimisation, the most suitable techniques adopted in various industries such as military sector are grouped in a set of interrelated models under the umbrella of the integrated logistics support ILS.

On the other hand, the growing complexity of petroleum systems is requiring more commitment from companies to optimise the financial and physical outputs of these capital assets. These effects are clearly observable in companies such as the ALGERIAN OIL COMPANY (SONATRACH). Consequently, the most significant current issue to address is the adoption of approaches which make it possible to maximise the output of these systems and to minimise their whole life cost.

10.2.2 REVIEW OF SECOND OBJECTIVE

Outline a theoretical framework for major ILS elements.

As reported in aviation and military fields, there is a competitive advantage gained by the development of ILS tools and a number of successful ILS implementations have been published. Notwithstanding this aspect, there are many obstacles in the adoption of ILS in the industry. Part of the challenge is that ILS elements are generally considered separately and not as a group as assumed in the ILS technique. The chapter 2 highlighted the fact that there is very little work in this area and a comprehensive optimisation of ILS elements to achieve a conclusive decision is needed. Furthermore, this chapter has shown that operational availability of complex systems is closely related to level of repair analysis (LORA) and spare part provisioning. This is true for most petroleum systems that are complicated and consisting of a lot of individual complex items, which, in turn require a suitable supportability management. The joint optimisation of LORA and spare part provision has been identified to be the way forward for cost-effective decisions to meet the operational objectives of the installed systems.

10.2.3 REVIEW OF THIRD OBJECTIVE

Investigate the influence of the different ILS elements on maintenance efficiency.

The examination of the ILS techniques and concepts has revealed that there is a huge potential when using the ILS elements to achieve cost-effective decisions for maintenance activities. Consequently, the third research objective relates to understanding the major ILS elements involved in maintenance optimisation. As mentioned above, a more thorough investigation concerning ILS elements has led to the identification of two ILS elements, namely LORA and spare part provisioning, to be important for maintenance optimisation.

For complex systems, up to 70% of the whole life cost WLC occurs during operation and decommissioning life cycle phases. Therefore, the maintenance costs, which represent a large percentage of operation cost, can be deeply affected by the support cost optimisation. In addition, it has been found in the literature review that the most important part of the whole life cost for maintenance activities stems from the decisions related to repair cost and the size of spare parts at hand. These decisions pertaining to the selection of repair network structure, the repair capacity to install, and the amount of spare parts at different repair shops have a great impact on the whole life cost. Even though the large commitment to WLC is made at the early phases, there is still opportunity to minimise costs during the operation phase. This is true for petroleum industry where the installed assets have a long useful life and their performance relies mainly on the maintenance and support decisions taken all over their life cycle.

10.2.4 REVIEW OF FOURTH OBJECTIVE

Develop a methodology, based on the use of LORA and spare part model,
capable of optimising maintenance activities.

Level of repair analysis (LORA) is a structured approach that investigates the cost effectiveness of repair strategy alternatives. It is generally carried out at the design phase or at the installation of complex equipment to identify the cost of both repair alternatives and repair levels by considering the costs of: spare parts inventory, manpower and support equipment (Blanchard, 1998). It considers cost of any repair option based on maintenance tasks, requested ability of manpower, MTBF of system items, repair equipment and economic criteria.

The distinguishing feature of LORA approach is its explicit consideration of repair, discard and move decisions for all system parts. The other important feature is that LORA decisions are optimised at different repair sites. The problem is therefore modelled as an integer programming. Given the large number of system parts and different level of repair locations, this problem is presented as NP-hard problem which is difficult to solve. Various techniques proposed in the literature have been reviewed and Genetic Algorithm optimisation techniques are found more effective and very suitable for NP-hard optimisation problem.

Additionally, the other issue for maintenance effectiveness is spare parts provision problems that occur in environments where complex equipment has to satisfy tough performance in terms of availability, reliability and costs. An extensive review showed that the VARI-METRIC based models (Sherbrooke, 1966) represent the most appropriate approach to deal with spare part supply in multi-echelon repair structure. However, these models suffer from a set of limitations when studying repair capacity. Therefore, the constraints for a limited repair capacity that can be incorporated in the VARI-METRIC model were examined in chapter 4. The focus was on multi-class M/G/k queue to enhance the spare parts estimates for a given availability threshold. The case studies carried out in this thesis have demonstrated that unlimited repair capacity underestimated the required amount of spare parts and the queueing model results can lead to better estimates compared to the reality.

10.2.5 REVIEW OF FIFTH OBJECTIVE

Derive suitable models suitable for petroleum industry.

A key aspect of the petroleum industry is that the systems are spread over a large area and require at the same time very prompt maintenance responses. As a result, more maintenance resources are needed. This can be done by possessing sufficient spare parts to ensure immediate replacement of failed items. Very high inventory levels which tie up large holding costs guarantee system functionality on the one hand, whereas on the other hand small number of spare parts may result in poor maintenance services or extremely costly reparation actions. Due to severe competition in petroleum industry, maintenance managers are forced to optimise their budget without jeopardizing system operation. Thus, a systematic methodology is required for ensuring defined levels of performance at lowest operation costs. Actually, most of the SONATRACH's maintenance support decisions are either based on system manufacturer procedure or past experiences, a need for a WLC approach arises. A spare parts optimisation combined with LORA analysis will offer a way to optimise the maintenance supportability while considering the annual budget requirements and the whole life costing.

10.2.6 REVIEW OF SIXTH OBJECTIVE

Combine the above models to form an integrated ILS tool.

In the ILS literature, the LORA analysis and the spare parts provision problem are usually solved sequentially. First, the LORA analysis is performed to deliver the optimal repair and discard decisions subject to the costs of repair and discard tasks. In this analysis, spare parts are considered to be available at all repair levels. After that, spare parts provision is optimised according to system availability and operation budget. Since the system availability can be enhanced either by the spare parts management or by the installed repair capacity, the model developed in this thesis was designed to concurrently find out the optimal levels of repair capacities and spare parts according to operation budget limit and system availability threshold. In addition, the model was used in order to analyse the tradeoffs between the spare parts costs and the repair costs.

10.2.7 REVIEW OF SEVENTH AND EIGHTH OBJECTIVES

Validate the developed framework

The validation and testing of the developed model plays an important role in verifying the efficiency and efficacy of the model when it is used in practice. In this research, a two-stage validation process was adopted based on benchmark comparison with case studies provided by the literature and the panel expert validation using a questionnaire. The judgement of maintenance experts and procurement engineers as well as the use of pilot studies related to the petroleum industry provided valuable point of view for refining and validating the model.

10.3 ORIGINAL CONTRIBUTIONS

By providing the answers to the key questions emerging from the problem statement of the research, has led into the development of the maintenance supportability framework. In this context, joint optimisation technique based on the integrated logistics support ILS approach looks quite promising. This approach is indeed able to improve decisions related maintenance management by effectively combining all support resources at the minimum whole life cost. This research work provides two significant contributions in the field of asset management.

- In literature, the integrated logistics support ILS has been effective in the whole life decisions of physical systems within the military industry. As a result, there have been a great amount of research endeavours to promote the practical use of this approach in some industries like: maritime and construction, among others. The contribution of this research has been to highlight the benefit to use ILS approach in the petroleum industry. The novel maintenance supportability framework, development in this thesis, has shown that ILS approach is able to lead to promising results in optimising the whole life maintenance cost. The numerical studies that have been carried out at the Algerian National Oil Company emphasizes the importance of ILS for cost optimisation and illustrates the advantages of ILS elements (level of repair analysis and spare part management) for maintenance efficiency. Finally, the framework has been applied with successful results which motivate maintenance engineers at the Algerian National Oil Company to use it in their daily professional life.

- Other important contribution of this thesis is a joint optimisation of two ILS elements, namely Level of Repair Analysis LORA and spare part management. This research has shown that an interaction effect between these two ILS elements can lead to suboptimal maintenance decisions when are optimised separately. These interactions motivate the need for joint optimisation to further optimise the whole life maintenance cost. Integrated and iterative optimisation techniques which have been used to solve LORA and spare part management simultaneously offer better optimal maintenance solutions. The joint optimisation therefore provides a clear improvement on current literature and industry practice and towards the integration of the whole ILS elements.

To sum up, this work has identified barriers to the practical adoption of the whole life costing and has demonstrated that the use of the integrated logistics support can overcome many of these hurdles and has provided a novel framework upon which such a technique can evolve. In short, this thesis has shown that, even though much more work needs to be done, ILS has the potential to result in an efficient of optimising the whole life cost of physical assets.

10.4 RECOMMENDATIONS FOR FUTURE WORK

Despite the practical advantages of the proposed framework, a number of possibilities for promising research have been identified during this work. This study address issues related to maintenance cost minimisation through the joint optimisation of two ILS elements. Due to the time limitation and data availability, continued research and application studies may include other ILS elements and other features of component reliability and maintainability. These are summarised in the following:

- Developing supplementary models to tackle situations when the failure rate may change with time. This may comprise algorithms that can integrate failure models based on Weibull and exponential functions.

- Another interesting development could be the combination of LORA with repair outsourcing, considering that repair can be performed within organisation's infrastructure, by external repair company or by manufacturer under warranty services.

- Extending the mode to integrate reliability centred maintenance RCM outcomes. This represents a situation in which system components are classified by category of criticality. When the number of components is very high (thousands), criticality analysis may decrease the optimisation problem size and therefore a reduction in calculation time.

- This research has focused on operation phase; it will be interesting to extend the use of LORA and spare part management to the design stage and study their impact component reliability issues and problems.

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APPENDIX A: TEST & VALIDATION QUESTIONNAIRE

Int

The following survey is a part of a PhD research work to develop a model for maintenance support optimisation. In order to minimise the whole life cost related to maintenance activities, level of repair analysis and spare part provision has been optimised jointly.

In this survey six key areas have been selected on the basis of the preliminary discussions. Multiple questions related to each of these areas have been developed to assess the validity of the model.

I would like to assure here that the data collected in this survey will only be used for statistical analysis of my research work. Participation in the survey is highly appreciated.

Taoufik BOUACHERA / the Algerian Petroleum Institute IAP
PhD Student
The Robert gortdon University
UK

The questionnaire consists of 6 areas of questions. Each contains a number of statements, which require a response. A response should be given by ticking the relevant box using the following scoring system:

(1) strongly disagree, (2) disagree (3) undecided

(4) agree (5) strongly agree.

Participant details

Name of work department ____________________

Location ____________________

Level of education ____________________

Level of computer skill ____________________

Experience:

What is your field of expertise

1- Maintenance ☐
2- Procurement ☐

1- How many years of experience do you have in the maintenance department ____________

Type of system have you been involved in its maintennace ____________

Current occupation ____________

2- How many years of experience do you have in the procurement department ____________

Type of system have you been involved in its spare part procurement ____________

Current occupation ____________

1 - Model Usefulness

		1	2	3	4	5
Effectiveness						
1	I can estimate required spare part using the model.					
2	I am successful in general in finding required data when using the model.					
3	Overall, the modle is useful in helping me					
4	I achieve what I want using the model					
5	The results I obtain from the model are useful.					
6	The model covers topics that I need.					
Efficiency						
1	It is easy to obtain the results that I need					
2	The model is easy to use in general.					
3	I can obtain the results in adequate time using the model					
4	The model is well designed to acheive what I need					
5	Using the model enhances the quality of my work					
Satisfaction						
1	Do the results obtained by the model look logic for me					
2	Can the results obtained by the model be applied					
3	Do the results differ largely from those E138					
4	Does not take a great deal of effort to become familair with the model					
5	The terminologies used on the model are easily understandable.					
6	Using the model makes it easier to do my work					
7	It was easy to learn to use the model					
8	I feel optimistic that themodel will be successful					

2 - Model Adaptability to environments

How satisfied are you with the adaptability features of this model to environments?

		1	2	3	4	5
1	Required input data are easily otained from organisation resources and archives					
2	Usefulness of the model output by the organisation					
3	Do missing data at your levele could be asily estimated?					
4	Applicability at different whole life phases					
5	How important to you are the benefits provided by to your orgnanisation?					

3 - Model Adaptability to culture of users

How satisfied are you with the adaptability features of this model?

		1	2	3	4	5
1	Familiarity with the theory					
2	Ease to manipulate the model					
3	It meets my needs.					
4	I quickly became skillful with it.					

4 - Weakness and Improvement

1 Based on pilot studies, what are the perceived advantages in using the model?

2 What are the characteristics of petroleumndustry contexts that need to be taken into account when applying the model?

3 What are the specific aspects that should be addressed when using the model?

5 - Comments

If you have any additional comments you wish to make about the model, please add them here

APPENDIX B: MAINTENANCE SUPPORT TOOL IN MATLAB ENVIRONMENT

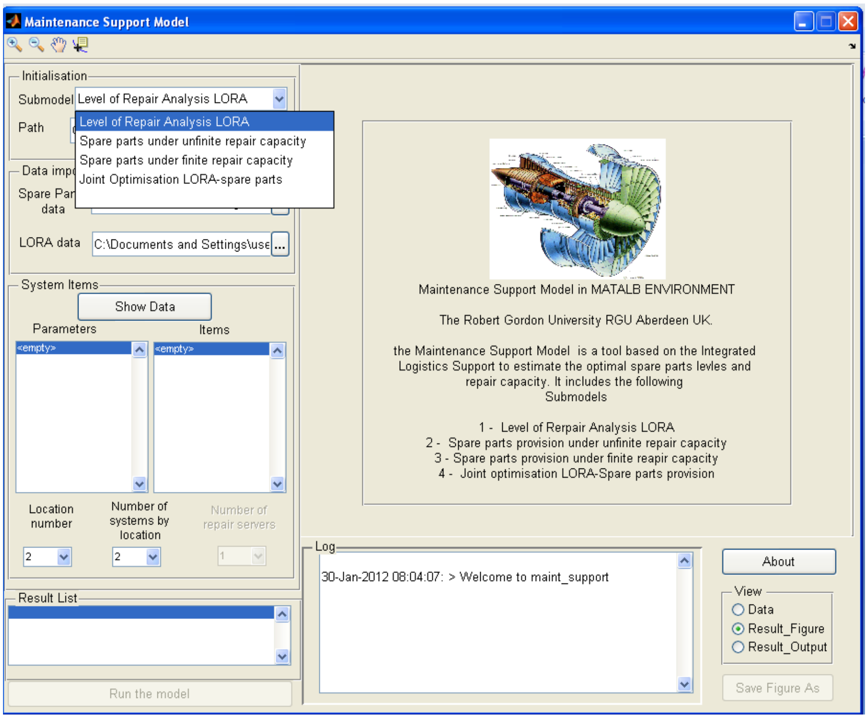
INTRODUCTION

Maintenance support tool developed in this research includes a set of algorithms for LORA analysis and spare parts control. This tool can be useful in the following tasks:

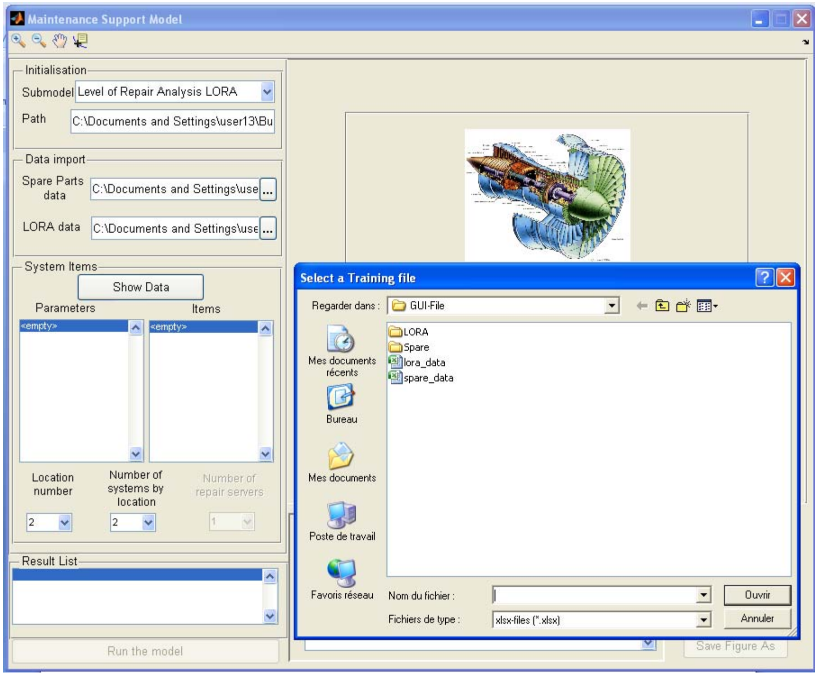
- Identification of repair decision according to repair network configuration using LORA analysis,
- Identification of spare part level when the repair capacity is considered unlimited,
- Identification of spare part level when the repair capacity is considered limited,
- Identification of spare part level when the repair trough a joint optimisation of LORA analysis and spare part models.

Starting the maintenance support tool

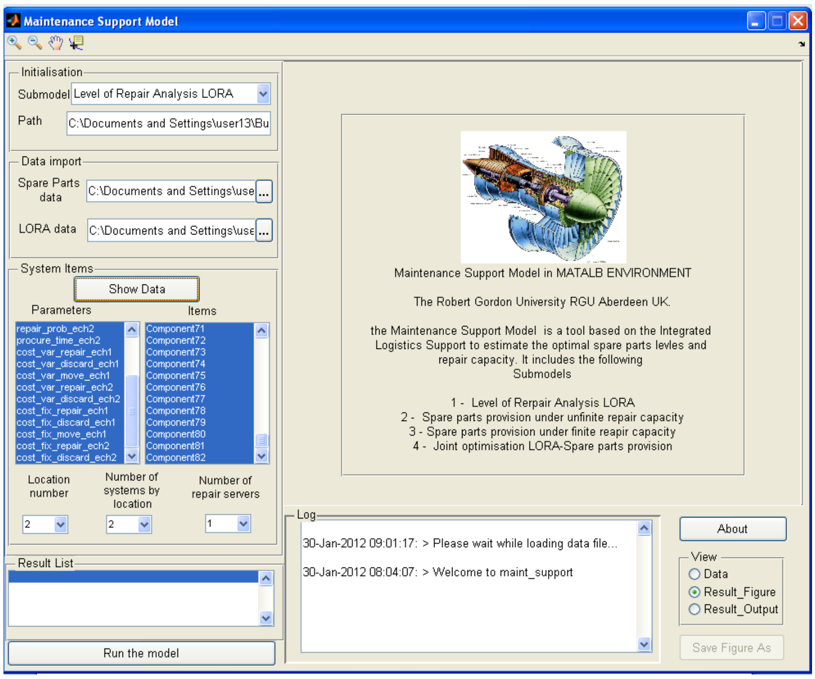
1. To start the tool type on the MATLAB file: GUI_launch.m located GUI in folder.
2. To select one of the tool sub-models, click on the upper pop-up menu as showed in the following figure.



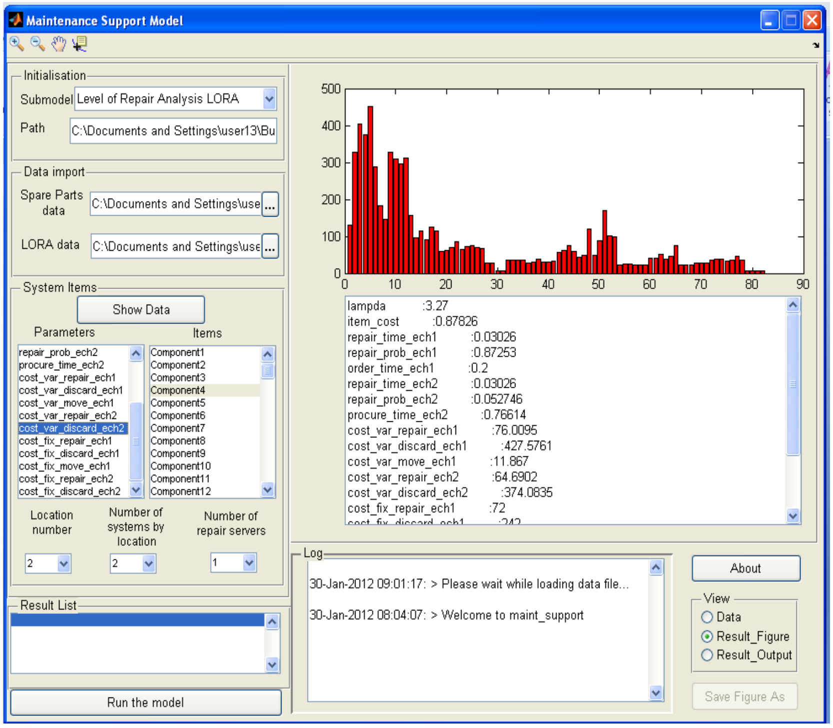
3. To load LORA and spare part data, click on the two pushbutton ”browse” in the data import field and select the file \GUI\GUI-File where the data is stored in Excel (*.xlsx) format. Then data is imported just by selecting the excel files.



The loaded Excel files contain one or more data matrices. The user can display the data by clicking on “Show Data” button.

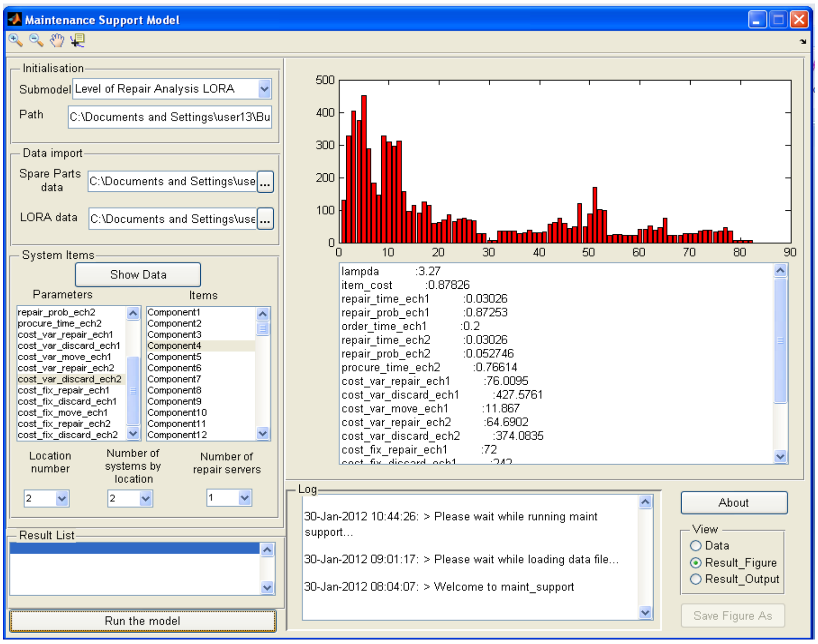


Two list-boxes namely parameters and items will allow the user to display cost and maintenance data for all items or for the chosen item. In addition, the button “Run the model” will be activated just after showing the data.



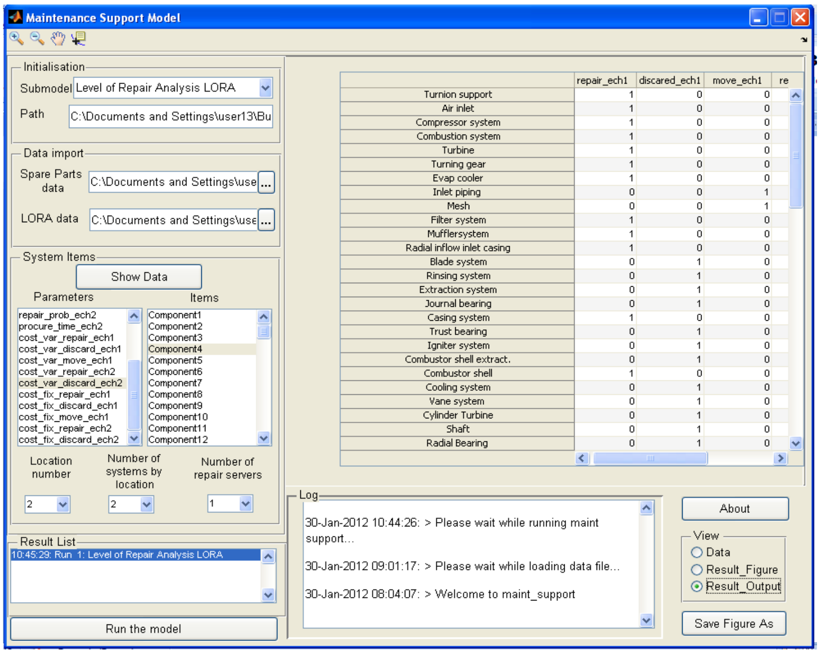
In the tool, repair location number, number of installed systems by location and the number of repair servers are set by choosing the values given in the pop-up menus.

4. After selecting the support sub-model and repair parameters, the user can click on the button "run the model" to start the algorithm for optimisation. During the computation, a message "Please wait while running maint-support model" appears in the window called LOG.

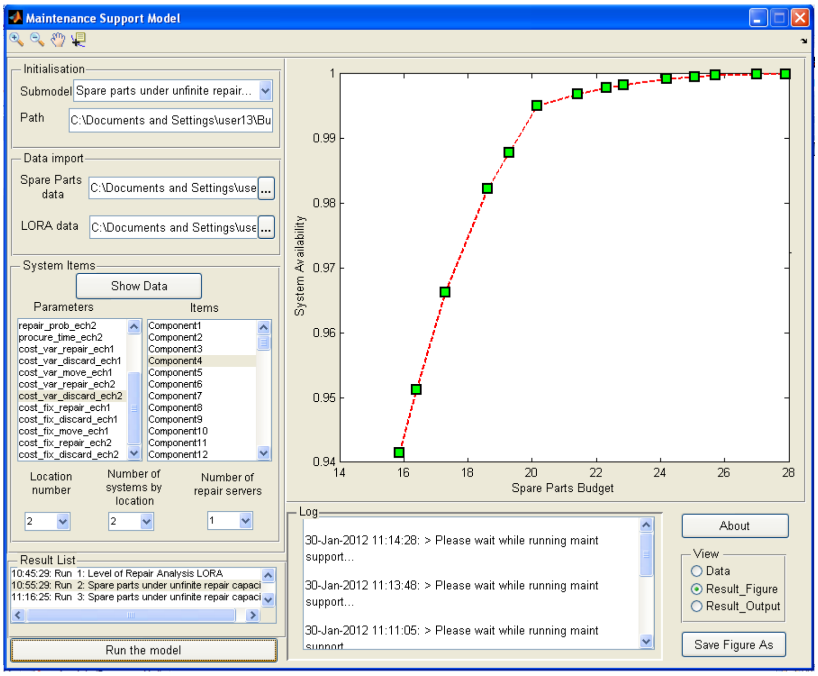


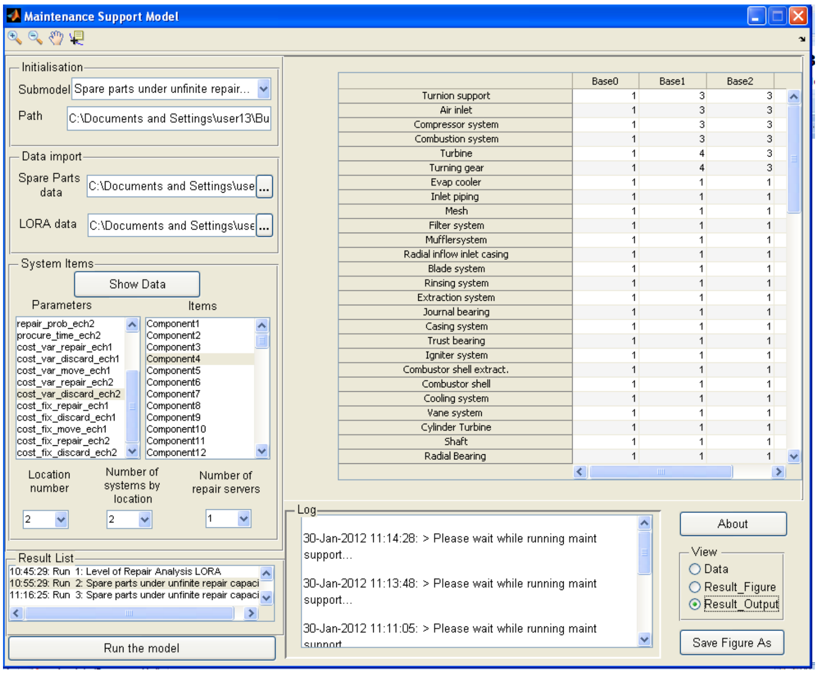
5. After few minutes (according to the size of the model) the result will be displayed by clicking on the radio buttons called "Result_Figure" and "Result_Output". The following figures show the outcome of running the model.

- The LORA analysis results represent the optimal repair decision for each item, i.e., where to conduct the repair and discard tasks in the repair network.



- The spare parts control results represent the optimal pairs of stock cost and system availability and the stock level by repair shop as shown on the following figures.





- Finally the user can save the figure result by clicking on the Button "Save figure as" for further use.

APPENDIX C: ABSTRACTS OF PUBLISHED PAPERS

Level of Repair Analysis based on Genetic Algorithm with Tabu Search

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Abstract

Genetic algorithms and their hybrid schemes have shown a great efficacy in solving large scale combinatorial problems in which solutions are highly time-consuming. The level of repair analysis (LORA), mathematically formulised by an integer programming model (IP), is very difficult to optimize by means of traditional optimization techniques due to a large number of decision variables involved. In this paper, a hybridised Genetic Algorithm with Tabu Search is presented and its application to solve Level of repair analysis (LORA) problem is investigated. The LORA, considered as an important tool for strategic system maintenance decision making, seeks to determine the location in the repair network at which a failed component should be discarded or repaired. The proposed algorithm is developed in order to determine the best repair decision combination. The efficacy of the algorithm is investigated in the context of a case study. The maintenance costs of a structure of three-echelon repair and multi-indenture is optimised under the condition that repair decision should be taken for all system items. Typical results have shown that the algorithm can effectively handle a real industrial sized case study with adequate optimisation computational time.

Keywords: Level of repair analysis, maintenance optimisation, Genetic Algorithms, Tabu Search.

Towards a Generic Framework for WholeLife Costing in the Oil Industry

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Abstract

There have been a number of endeavours to establish and implement the whole life costing (WLC) technique in several industries. Many researchers recognize that the lack of readily available WLC data constitutes the most important barrier that inhibits its successful practical implementation. Data breakdown structure plays, therefore, an important role in promoting the adoption of WLC. These arguments are especially true for oil and gas assets in which operation, maintenance and support activities represent the bulk of their whole life costs. This paper focuses on addressing this limitation by discussing the suitability of incorporating integrated logistics support (ILS) with WLC. This Paper is first in a series to report an on-going PhD project to develop a generic framework for whole life costing applications in the oil industry. The main issues inherent to the development of this framework have been considered. Firstly, a literature review covering the WLC and ILS techniques are carried out. Then, the necessity of including these techniques into current oil and gas asset management practice is discussed. Finally, directions for future research are introduced.

Keywords: cost breakdown structure, integrated logistics support, oil and gas assets, whole life costing.