PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE
SCHOOL OF ENGINEERING

INTEGRATED MODELS FOR CRITICAL SPARE PARTS MANAGEMENT IN ASSET INTENSIVE INDUSTRIES

DAVID R. GODOY RAMOS

Thesis submitted to the Office of Research and Graduate Studies
in partial fulfillment of the requirements for the Degree of
Doctor in Engineering Sciences

Advisors:
RODRIGO PASCUAL JIMÉNEZ
PETER F. KNIGHTS

Santiago de Chile, December 2014

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To Rosita, the best mother in the world,
to Carla, my beautiful and unconditional partner,
and to all my family, for their endless support.
To God, for holding my hand every time
I have been about to fall down.
To all those who, despite any humble origins,
dream of making a difference.

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ABSTRACT

Spare parts are of key importance for equipment intensive industries –such as Mining, Aeronautic, or Defense– since their role is to efficiently support the operation of critical equipment and enhance system performance, thereby meeting business success.

Organizations within such industries face continuous challenges to improve utilization, reduce costs, and manage risks. Miscalculating these decisions might lead to overstress on equipment and associated spare components, thus affecting availability, reliability, and system throughput. Critical spare parts therefore merit complex modeling. However, an asset management perspective –a systemic means of optimally managing resources to ensure sustainable business goals– has not been integrated into every vital decision stage of spares policies.

In an effort to include this type of approach, this research has modeled the spares process from selection of the most important resources to supply chain requirements. The general objective of this thesis is to develop an asset management-based framework to optimize the life cycle of critical spare parts by integrating five key decision areas, namely: prioritization, ordering, replacement, maintenance outsourcing, and pool allocation. These areas are crucial to performance excellence for asset intensive firms.

The resulting support system is documented by five ISI journal articles dealing with the key decision areas. The methodology is illustrated by an introduction, real-industry case studies, and sequential addressing of aims and contributions for each appended paper. They are summarized as follows. First, **Paper I** *"Throughput centered prioritization of machines in transfer lines"* delivers the graphical tool called *System Efficiency Influence Diagram*, which prioritizes the critical resources for system throughput considering intermediate buffers. Second, **Paper II** *"Critical spare parts ordering decisions using conditional reliability and stochastic lead time"* introduces the concept of *Condition-Based Service Level* to define the spares ordering time at which the system operation

is sufficiently reliable to withstand lead time variability. Third, **Paper III** *"Value-based optimization of intervention intervals for critical mining components"* shows the influence of business value for accelerating versus postponing the optimal epoch to perform the spares replacement. Fourth, **Paper IV** *"Optimizing maintenance service contracts under imperfect maintenance and a finite time horizon"* sets contract conditions for motivating service receivers and external providers to reach win-win coordination. Lastly, **Paper V** *"A decision-making framework to integrate maintenance contract conditions with critical spares management"* profitably allocates the components pool within the maintenance service contract. The enriched models and graphical tools developed in these papers are useful for operations design and major planning.

This thesis provides asset managers with integrated decision-making models to optimize the life cycle of critical spare parts under a systemic perspective. The research builds an interesting bridge across the areas of condition-based maintenance, outsourcing coordination, and joint decisions on reliability engineering and stockholding policies. This interaction works toward modeling the spares process key decision stages in order to efficiently enhance system performance within equipment intensive industries. In summary, the methodology contributes to continuous improvement and firm profitability since business-oriented approaches are included. This thesis has confirmed the value of moving from a maintenance viewpoint biased by single interests to a perspective considering the whole system: the physical asset management perspective.

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Keywords: Critical spare parts management, prioritization, ordering, replacement, outsourcing, pool allocation, integrated models, condition-based maintenance, supply chain, equipment intensive firms, asset management.

PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE
ESCUELA DE INGENIERÍA

MODELOS INTEGRADOS PARA LA GESTIÓN DE REPUESTOS CRÍTICOS EN INDUSTRIAS DE USO INTENSIVO DE ACTIVOS

Tesis enviada a la Dirección de Investigación y Postgrado en cumplimiento parcial de los requisitos para el grado de Doctor en Ciencias de la Ingeniería

DAVID R. GODOY RAMOS

RESUMEN

Los repuestos son de importancia clave para industrias de capital intensivo –como Minería, Aeronáutica, o Defensa– debido a su rol de soportar eficientemente la operación de equipos críticos para mejorar el rendimiento del sistema, logrando así el éxito de negocio.

Las organizaciones dentro de tales industrias enfrentan desafíos continuos para aumentar utilización, reducir costos, y manejar riesgos. La falta de guía en estas decisiones puede conducir a una sobre-exigencia de equipos y componentes asociados, afectando disponibilidad, confiabilidad, y productividad del sistema. Los repuestos críticos ameritan, por lo tanto, un modelado complejo. Sin embargo, una perspectiva de gestión de activos físicos –un método sistémico para el manejo óptimo de recursos que garantice sustentablemente objetivos de negocio– no ha sido integrada en cada etapa vital de decisión de las políticas de repuestos.

En un esfuerzo por incluir tal enfoque, esta investigación ha modelado el proceso de repuestos desde la selección de recursos hasta requerimientos de la cadena de abastecimiento. El objetivo general de esta tesis consiste en desarrollar un esquema basado sobre la gestión de activos para optimizar todo el ciclo de vida de los repuestos críticos, mediante la integración de cinco áreas claves de decisión: priorización, pedido, reemplazo, externalización, y manejo de grupos de componentes. Estas áreas son cruciales para la excelencia en desempeño de las empresas de capital intensivo.

El sistema de soporte resultante es documentado por cinco artículos en revistas ISI que tratan tales áreas claves de decisión. La metodología es ilustrada a través de una introducción, casos de estudios reales, y el logro secuencial de objetivos y contribuciones de cada *paper* adjunto. Éstos se resumen a continuación. Primero, **Paper I** *"Throughput centered prioritization of machines in transfer lines"* entrega la herramienta gráfica denominada *Diagrama de Influencia para la Eficiencia de Sistema*, la cual prioriza los recursos críticos para el rendimiento considerando acumuladores intermedios.

Segundo, **Paper II** *"Critical spare parts ordering decisions using conditional reliability and stochastic lead time"* introduce el concepto de *Nivel de Servicio Basado sobre Condición* para definir el momento de pedido de repuestos en que la operación es suficientemente confiable para soportar la variabilidad de los tiempos de entrega. Tercero, **Paper III** *"Value-based optimization of intervention intervals for critical mining components"* muestra la influencia del valor de negocio para anticipar o posponer la época óptima para reemplazar los componentes. Cuarto, **Paper IV** *"Optimizing maintenance service contracts under imperfect maintenance and a finite time horizon"* establece las condiciones contractuales que motivan a clientes y proveedores externos de servicios para alcanzar una coordinación ganar-ganar. Por último, **Paper V** *"A decision-making framework to integrate maintenance contract conditions with critical spares management"* asigna rentablemente el *pool* de componentes dentro del contrato de servicios de mantenimiento. Los modelos enriquecidos y herramientas gráficas desarrolladas en estos *papers* son útiles para diseño de procesos de planta y planificación de largo plazo.

Esta tesis provee a los gestores de activos con modelos integrados de soporte de decisiones para optimizar el ciclo de vida de repuestos críticos bajo una perspectiva sistémica. La investigación construye un interesante puente a través de las áreas de mantenimiento basado sobre condiciones, coordinación en externalización, y decisiones conjuntas de ingeniería de confiabilidad y políticas de abastecimiento. Esta interacción responde al objetivo de modelar las etapas clave de decisión del proceso de repuestos y mejorar eficientemente el rendimiento del sistema en industrias intensivas de capital. En resumen, la metodología contribuye al mejoramiento continuo y la rentabilidad de la empresa puesto que se incluyen enfoques orientados al negocio. Esta tesis ha confirmado el valor de pasar desde una visión de mantenimiento sesgada por intereses particulares hacia una perspectiva que considere todo el sistema: la perspectiva de gestión de activos físicos.

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Palabras Claves: Gestión de repuestos críticos, priorización, pedido, reemplazo, externalización, asignación, modelos integrados, mantenimiento basado sobre condiciones, abastecimiento, firmas de capital intensivo, gestión de activos.

LIST OF PAPERS

This thesis is documented by the following papers, which will be referred to in the text by the Roman numerals assigned to them.

Paper I Pascual, R., Godoy, D.R., & Louit, D. (2011). Throughput centered prioritization of machines in transfer lines. *Reliability Engineering and System Safety*, *96*(10), 1396–1401.
ISI journal | Impact factor (2011): 1.770 | 5-year Impact factor: 2.170.

Paper II Godoy, D.R., Pascual, R., & Knights, P. (2013). Critical spare parts ordering decisions using conditional reliability and stochastic lead time. *Reliability Engineering and System Safety*, *119*(11), 199–206.
ISI journal | Impact factor (2013): 1.901 | 5-year Impact factor: 2.441.

Paper III Godoy, D.R., Knights, P., & Pascual, R. (2014). Value-based optimization of intervention intervals for critical mining components. *Reliability Engineering and System Safety (Submitted).*

Paper IV Pascual, R., Godoy, D.R., & Figueroa, H. (2012). Optimizing maintenance service contracts under imperfect maintenance and a finite time horizon. *Applied Stochastic Models in Business and Industry*, *29*(5), 564–577.
ISI journal | Impact factor (2012): 0.544 | 5-year Impact factor: 0.786.

Paper V Godoy, D.R., Pascual, R., & Knights, P. (2014). A decision-making framework to integrate maintenance contract conditions with critical spares management. *Reliability Engineering and System Safety*, *131*(11), 102–108.
ISI journal | Impact factor (2014): 2.048 | 5-year Impact factor: 2.593.

1. INTRODUCTION

Spare parts play an essential role in supporting critical equipment to efficiently enhance system performance, thereby meeting the business premise of succeeding in asset intensive industries such as Mining, Aeronautic, and Defense, among others.

Efficient spares management is a strategic driver for companies in which success strongly relies on equipment performance. As competitive organizations, asset intensive industries face continuous challenges to improve utilization, reduce costs, and manage risks. However, misguiding these challenges may cause overstress on machines and related components, affecting availability, reliability, and more importantly, system throughput. Some of those assets are particularly critical for operational performance. This criticality, as a function of equipment use, is defined by its relevance in sustaining safe and efficient production (Dekker, Kleijn, & De Rooij, 1998). The operation of equipment that fulfills such characteristics is supported by critical spare parts (Louit, 2007). Critical spare components are linked to large investments, high reliability requirements, extended lead times, and plant shutdowns with severe impacts on operational continuity (Godoy, Pascual, & Knights, 2013). Decision-making models to deal with critical spare parts are therefore essential to balance both operational and financial goals.

The core of this research is on those critical spares that affect production and safety, are expensive, with high reliability requirements, and are usually associated with higher lead times. Hence, these spare components merit complex modeling. These items are also considered critical when they support essential equipment in an operational environment (Louit, 2007). Henceforward, all spare parts that meet these characteristics will be called “Condition Managed Critical Spares”, or just CMS. Figure 1-1 shows a diagram of the spare parts that we are focusing on. CMS are repairable, however their repair times are generally slower than supplier lead times. This particularity turns these

CMS into non-repairable spare parts for the purposes of this model. As CMS are not always available in store, CMS condition is monitored as a mitigation measure of its criticality in the operation.

Physical Asset Management (PAM) is an effective approach in pursuit of ensuring system performance requirements. PAM is simply defined as the optimal way of managing assets to achieve a desired and sustainable outcome (International Organization for Standarization, 2012; British Standards Institution, 2008). PAM has evolved from a maintenance perspective confined by reactive tasks to a strategic dimension that covers every stage in the life cycle of systems (Campbell, Jardine, & McGlynn, 2011; Jardine & Tsang, 2006). An example of this wider context includes an integrated model for systematic decisions regarding resources critical to business success. This thesis attempts to analyze the entire spare parts management process, from selection of the most important resources to logistic outsourcing considerations, *i.e.* common but critical decisions faced within the capital intensive industry. Although the focus is primarily on the Mining industry, the extension to other asset-intensive industries is straightforward. Expecting to improve the applicability, the theory is complemented by real industry-based case studies.

The hypothesis is the following: “An integral critical spare part modeling approach that includes every stage in the asset life cycle must efficiently ensure that business requirements have been achieved”. Nevertheless, an asset management perspective – perceived as a systemic means of optimally handling resources to ensure sustainable business goals– has not been integrated into every vital decision stage of spares policies.

Therefore, **the general objective of this thesis is to develop an asset management-based framework to optimize the entire life cycle of spare parts by integrating five key decision areas, which are crucial to performance excellence of equipment intensive firms.** This integrated scheme includes the following stages: prioritization, ordering, replacement, maintenance outsourcing, and pool allocation. In particular, it is intended:

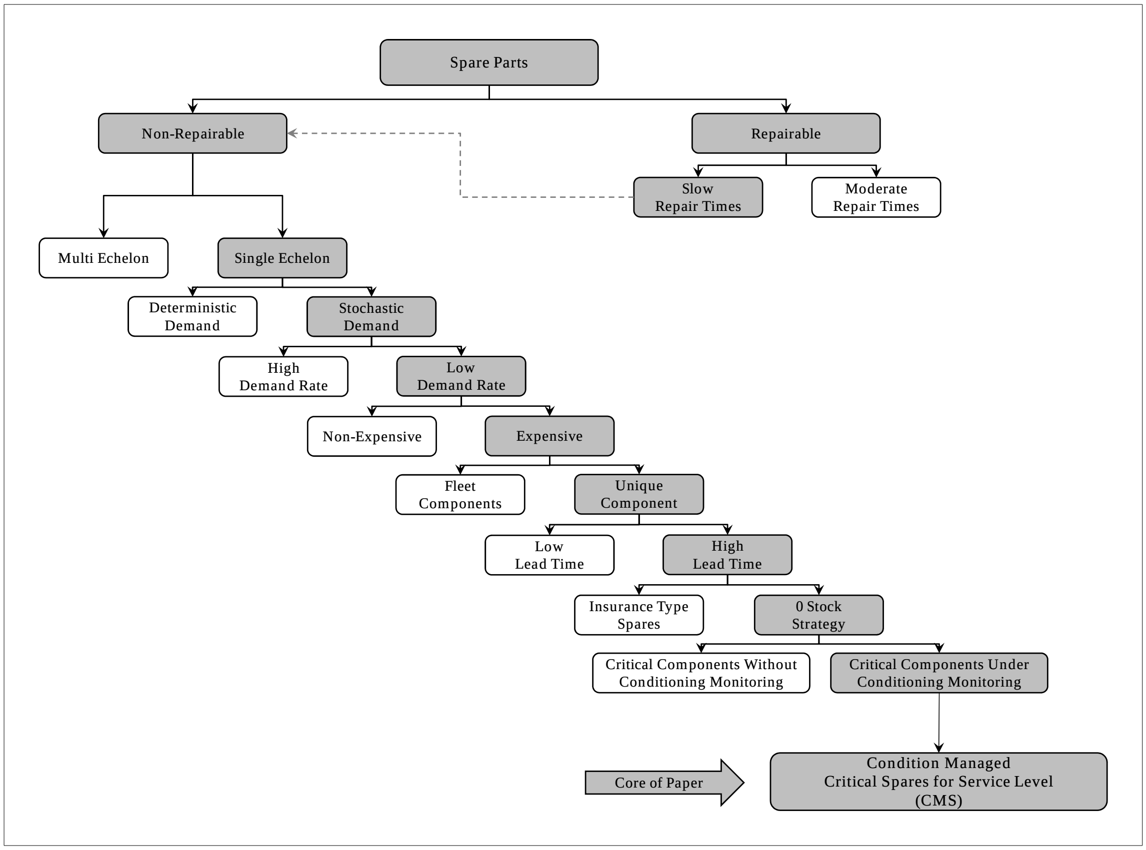

Figure 1-1: Condition managed critical spare parts

1. To formulate new and enriched mathematical models for each stage of spares management.
2. To create user-friendly tools based on cost, risk, and benefit, to efficiently guide decision-makers.
3. To consolidate the developed tools into integrated decision-making models under the asset management strategy.

Interestingly, the research builds a bridge across the areas of throughput requirements, condition-based maintenance, logistics, business value, outsourcing coordination, and joint decisions on reliability engineering and stockholding policies.

The resulting support system is the product of five ISI journal articles documenting these key decision areas. These articles are listed in the “List of Papers” chapter. The thesis is illustrated by a summary, real-industry case studies, and sequential addressing of aims for each appended article. These papers are summarized in the “Thesis Scope” section. Their link and contribution to the final result of the thesis –namely, the integrated decision-making models– are outlined in the “Thesis Structure” section. The details are presented in each chapter throughout the complete document.

The rest of this thesis is organized as follows. Chapter 2 handles the prioritization problem in production lines with intermediate buffers. Chapter 3 introduces the concept of *Condition-Based Service Level* to determine the spare ordering time when an operation is reliable and can withstand the lead time variability. It also helps to define insurance spares. Chapter 4 discusses the real value of whether to accelerate or postpone a spare replacement in order to maximize business objectives, by satisfying both reliability constraints and time windows. Chapter 5 sets contract conditions that motivate service receivers and external providers to continually improve their maintenance services and reach a win-win coordination. Chapter 6 delivers an original joint value –preventive interval and stock level– to set the optimal agreement to profitably allocate the components pool within the maintenance service contract. Subsidization bonuses and break-even fees are also estimated to induce service providers to adjust their policy when needed. Finally, Chapter 7 encloses the conclusions and delivers areas for further research.

1.1 Thesis Scope

The thesis scope is based on five key themes concerning to the entire process of critical spare parts management, which are summarized below.

1.1.1 Throughput-based prioritization of systems and spare parts

In an environment of scarce resources and complex production systems, prioritizing is key to confront the challenge of physical asset management. In the literature, there exist a number of techniques to prioritize maintenance decisions that consider safety, technical and business perspectives. However, the effect of risk-mitigating elements –such as intermediate buffers in production lines– on prioritization has not yet been investigated in depth. In this line, the work proposes a user-friendly graphical technique called the *System Efficiency Influence Diagram* (SEID). Asset managers may use SEID to identify machines that have a greater impact on the system throughput, and thus set prioritized maintenance policies and/or redesign buffers capacities. The tool provides insight to the analyst as it deconstructs the influence of a given machine on system throughput as a product of two elements: (i) the system influence efficiency factor and (ii) the machine unavailability factor. We illustrate its applicability using three case studies: a four-machine transfer line, a vehicle assembly line, and an open-pit mining conveyor system. The results confirm that machines with greater unavailability factors are not necessarily the most important for production line efficiency, as is the case when no intermediate buffers exist. As a decision aid tool, SEID emphasizes the need to move to a systems engineering perspective rather than a maintenance vision focused on machine availability.

1.1.2 Critical spare parts ordering decisions

Asset-intensive companies face great pressure to reduce operating costs and increase utilization. This scenario often leads to overstress on critical equipment and associated spare parts, affecting availability, reliability, and system performance. As these resources considerably impact on financial and operational structures, there is a high demand for decision-making methods for spare parts process management. We proposed an ordering decision-aid technique which uses a measurement of spare performance based on the stress-strength interference theory, which we have called *Condition-Based Service Level* (CBSL). We focus on *Condition Managed Critical Spares* (CMS), namely, spares which are expensive, highly reliable, with higher lead times, and are not available in store. As a mitigation measure, CMS are under condition monitoring. The aim of the paper is to orient the decision time for CMS ordering or to just continue the operation. The paper presents a graphic technique considering a rule for decision based on both condition-based reliability function and a stochastic/fixed lead time. For the stochastic lead time case, results show that the technique is effective for determining when the system operation is reliable and can withstand the lead time variability, satisfying a desired service level. Additionally, for the constant lead time case, the technique helps to define insurance spares. In conclusion, the ordering decision rule presented is useful to asset managers for enhancing the operational continuity affected by spare parts.

1.1.3 Replacement intervals for critical spare components

Highly competitive industries, such as Mining, face constant pressure for continuous improvement. This increasing need for efficiency demands the use of reliability and benefit models, especially for significant investment equipment and components. Critical major components –e.g. mill liners, shovel swing transmissions or haul truck engines– are related to lengthy shutdowns with a considerable impact on financial structure. In this context, cost optimization is a widely-used principle for scheduling component replacements. However, this practice does not traditionally involve considering external factors of interest –such as business-market conditions– which can radically alter decisions. To overcome this limitation, we have proposed a criterion based on the estimation of revenues –under several commodity price scenarios– both at the time of component intervention and during the major shutdown time window. This work aims to guide the decision about the best moment to replace, considering the maximization of value-added rather than simply minimization of costs. The paper presents a model to evaluate this optimal value by estimating the net benefit, as it is subjected to a certain discount rate, considering the copper price, component survival probabilities (using Condition-Based Maintenance, CBM), cost and expected downtime. The results show the influence of business objectives in identifying the real value of waiting for the right epoch to perform an intervention, in order to optimize the decision benefit and satisfy both reliability constraints and time windows. In conclusion, business profitability opportunities increase when maximization of value-added is included as part of the complete asset management system.

1.1.4 Maintenance outsourcing under realistic contract conditions

When companies decide to outsource their services, the most important arguments usually include: focus on the core business, ability to access high quality services at lower costs, and risk transfer sharing. However, contractual agreements have typically followed structures in which both the client and the contractor attempt to maximize their own expected profits in a non-coordinated way. Although previous research has considered supply chain coordination by means of contracts, it has included unrealistic hypotheses such as perfect maintenance and/or infinite time-span contracts. The present work overcomes these limitations by studying contractual conditions in order to coordinate the supply chain through a preventive maintenance strategy that maximizes the total expected profit for both parties in a finite time-span contract. This paper presents a model to establish such conditions when maintenance is imperfect and the contract duration is fixed through a number of preventive maintenance actions along a significative part of the asset life cycle under consideration. We also study the cases where the owner is profit-centered or service-centered, while the contractor is profit-centered. Results show that players can achieve a greater benefit than what could have been obtained separately. The formulation leads to a win-win coordination under a set of restrictions that can be evaluated *a priori*. The proposed contract conditions motivate stakeholders to continually improve their maintenance services to reach channel coordination, where both contract parties obtain higher rewards.

1.1.5 Pool allocation of critical spare components

Maintenance outsourcing is a strategic driver for asset intensive industries pursuing supply chain performance enhancement. Spare parts management plays a relevant role in this premise since it has a significant impact on equipment availability, and hence on business success. Designing critical spares policies might therefore seriously affect maintenance contracts profitability, yet service receivers and external providers traditionally attempt to benefit separately. To coordinate both chain parties, we investigated whether the spare components pool should be managed in-house or contracted out. This paper provides a decision-making framework to efficiently integrate contractual conditions with critical spares stockholding. Using an imperfect maintenance strategy over a finite horizon, the scheme maximizes chain returns whilst evaluating the impact of an additional part to stock. As a result, an original joint value –preventive interval and stock level– sets the optimal agreement to profitably allocate the components pool within the service contract. Subsidization bonuses on preventive interventions and pooling costs are also estimated to induce the service provider to adjust its policy when needed. The proposed contractual conditions motivate stakeholders to continuously improve maintenance performance and supply practices, thus obtaining higher joint benefits.

1.2 Relevant Literature

The following literature review is structured as the aforementioned five key decision areas.

1.2.1 Throughput centered prioritization in the presence of buffers

Pareto analysis has been commonly used to select the components and most critical failure modes of a system. A limitation of this approach is that it uses a single criterion to prioritize. In maintenance management, availability is a typical indicator. This indicator does not allow to ensure whether the cause of failure is a high frequency (reliability) or long downtime (maintainability). To help overcome this problem, Labib (1998) suggests the *Decision Making Grid*. It uses a diagram that includes frequency and downtime, allowing the monitoring of equipment and indicating the appropriate action. An example of a non-graphical technique is the *Analytic Hierarchy Process*, which uses pairwise comparisons and relies on the judgements of experts to derive priority scales (Saaty, 2008). A disadvantage of using this method is that in situations with a sizeable number of alternatives, the required comparison step can be unwieldy and excessive resource consuming. In the case of *Failure Mode and Effect Analysis* (FMEA), the rating to calculate the priority of the failures is called *risk priority number* (Franceschini & Galetto, 2001), *severity* (Pasquini, Pozzi, & Save, 2011) and/or *criticality rank* (Selvik & Aven, 2011), which is worked out by the product of different ratings: frequency, consequence, detectability, etc. Nonetheless, in many cases the estimation of these factors can be highly subjective. A more advanced technique is proposed by Knights

(2004) through the *Jack Knife Diagram* (JKD), a logarithmic scatter plot that involves simultaneously three performance indicators: frequency, downtime, and unavailability. Using JKD, it is possible to classify failures as acute and/or chronic. Acute failures indicate problems in inspections, resource availability, preventive maintenance, among others. Furthermore, chronic failures indicate problems in equipment operation and materials quality. The JKD technique only considers time based information, excluding economic effects which certainly affect prioritization in a business context. In order to surpass this limitation, Pascual, Del Castillo, Louit, and Knights (2009) propose the *Cost Scatter Diagram* (CSD) that incorporates the economic dimension and includes JKD analysis as a special case. This technique explores the opportunities for improvement using business-oriented performance indicators, such as: total costs, direct costs, availability, frequency, and downtime. None of the aforementioned tools explicitly consider that in production systems there exist elements that mitigate the impact upon the occurrence of unanticipated events (i.e. failures), and even expected (scheduled maintenance). These elements range from stockpiles (buffers), redundant equipment, availability of *in situ* spare parts, to insurance against all risks, to mention some of them.

A production line may have none, one, or many intermediate buffers. If any of the machines of the line fails, the buffers can eliminate/mitigate the idleness that produces the flow discontinuity, enhancing the production rate. While larger buffers can absorb longer interruptions, they also increase inventory costs (Burman, Gershwin, & Suyematsu, 1998). This observation justifies inventory reduction strategies such as the well-known *Just in Time* (Shah & Ward, 2003). As the interruption in production flows may generate costly consequences, the reduced presence of buffers in plants has created the need to continuously improve maintenance strategies (and priority setting needs) (Crespo & Gupta, 2006).

In the context of decision making for production systems, there is a relevant difference between maintenance management and physical asset management. According to PAS-55 (British Standards Institution, 2008), asset management is defined as: *systematic and coordinated activities and practices through which an organization optimally manages its assets, and their associated performance, risks and expenditures over their lifecycle for the purpose of achieving its organizational strategic plan*. In maintenance management, a common performance indicator is machine availability. Although it may seem suitable that the maintenance function focuses on improving the equipment availability, it may also lead to reduced care on production efficiency and to a biased business vision. Asset management avoids optimizing indices separately and advises applying a global perspective considering the implications of maintenance policies within the organization strategic plan (Crespo, Gupta, & Sánchez, 2003). According to Li, Blumenfeld, Huang, and Alden (2009), throughput is relevant for the design, operation and management of production systems, because it measures the system production volume and represents the line efficiency. Then, a key performance indicator for asset managers may be the system throughput or, complementarily, the production efficiency. The latter sets a need to characterize the system efficiency, and thus to provide a systems engineering management perspective. Simulation based efficiency estimation provides a guide for incorporating realistic conditions to evaluate system level improvements. As example, Murino, Romano, and Zoppoli (2009) use simulation to consider the effect of condition based maintenance. However, time, cost and expertise required to develop simulation models may impose a barrier for their application in industry (Kortelainen, Salmikuukka, & Pursio, 2000; Louit, 2007; Murino et al., 2009). Analytical modeling may offer a simpler and cheaper alternative to simulation. One example is the DDX method (Dallery, David, & Xie, 1989), which considers transfer lines with unreliable machines and finite buffers. In the case of a homogeneous line, the behavior is approximated by a continuous flow model and decomposing the system into sets of two-machine lines (for which closed solution exist). The decomposition results in a simple and fast algorithm which provides performance indicators, such as expected throughput and buffer levels. Experimental results have shown that this approximate technique is very accurate. In the case of a non-homogeneous line, a simple method is introduced to transform it into a homogeneous line. In addition to DDX, there exist a number of analytical models to estimate the system throughput. A review of these methods can be found in Li et al. (2009).

1.2.2 Ordering decisions using conditional reliability and stochastic lead time

Spare parts play a fundamental role in the support of critical equipment. In a typical company, approximately one third of all assets corresponds to inventories (Díaz & Fu, 1997). Of these assets, critical spare parts have special relevance because they are associated with both significant investment and high reliability requirements. As an example, spares inventories sum up above US$ 50 billion in the airlines business (Kilpi & Vepsäläinen, 2004). The mismanagement of spare parts that support critical equipment conduces to considerable impacts on financial structure and severe consequences on operational continuity. The improvement of key profits on both logistics and maintenance performance can be achieved by inventory management of costly components, which have extremely criticality on equipment-intensive industries (Braglia & Frosolini, 2013). Therefore, efficient decisions about spare-stocking policies can become essential in the cost structure of companies. In order to provide an efficient spare management performance, a suitable ordering strategy can be relevant. A spare part classification scheme becomes necessary to set optimal policies for those spares that may affect the system the most, and at the least effort.

The need for spare parts inventories is dictated by maintenance actions (Kennedy, Wayne Patterson, & Fredendall, 2002). In addition, maintenance strategy can be treated by Condition-Based Maintenance (CBM). In this case, models incorporate information about equipment conditions in order to estimate the conditional reliability. This information comes from, for instance, vibrations measurements, oil analysis, sensors data, operating conditions, among others. These measures are called covariates. Covariates may be included on the conditional reliability using the Proportional Hazards Model (PHM) (Cox, 1972), which allows combining age and environmental conditions. In the interaction between operational environment and equipment, while age can be relatively easy to notice, deterioration can be measured by conditions assessment (Amari, McLaughlin, & Pham, 2006). Therefore, CBM becomes useful to set maintenance policies even with different levels of monitoring restrictions. Compared to usual time-based maintenance strategies, condition monitoring systems offer significant potential to add economic value to spares management performance (Van Horenbeek, Van Ostaeyen, Duflou, & Pintelon, 2013).

Lead time is another important aspect to consider in spare parts ordering. The random time between fault event and the actual component failure may cause system performance deteriorations (Das & Acharya, 2004). Nonetheless, it also provides a opportunity window to set replacement policies. Logistically, there are also delays between the order of spares and their arrival (Wang, Chu, & Mao, 2009). This situation is even more crucial when spare parts are critical, since they are not always available at the supplier store. Customs delays and the need of special transport are a source of significant lead times;

moreover, when dealing with complex equipment parts made to order, lead times may exceed a year (Van Jaarsveld & Dekker, 2011). The lack of these items because of a delay in delivery (and their consequent installation) may have severe consequences in the operational continuity.

Previous works have treated the decision-making process using CBM, for instance: research deals with a continuously deteriorating system which is inspected at random times sequentially chosen with the help of a maintenance scheduling function (Dieulle, Berenguer, Grall, & Roussignol, 2003). There is also research obtaining an analytical model of the policy for stochastically deteriorating systems (Grall, Berenguer, & Dieulle, 2002). However, spare parts issues are not included on those papers. Furthermore, there are several researches for CBM policies that consider unlimited spare parts which always are available (Amari & McLaughlin, 2004). Nevertheless, the focus of this paper is on critical spare parts which are, precisely, not available in store. According to (Wang, Chu, & Mao, 2008), few existing ordering and replacement policies are proposed in the context of condition-based maintenance. In fact, the work described by Wang et al. (2008) aims to optimize CBM and spare order management jointly. Kawai (1983a) and Kawai (1983b) consider optimal ordering and replacement policy of a Markovian degradation system under complete and incomplete observation, respectively. However, the difference between this thesis and the works stated above is the need to install a user-friendly technique to decision-making process for asset managers in order to improve the spare parts management considering the unique characteristics of CMS. In accordance with current industrial requirements, a graphical tool of this type could be readily implemented. Spare parts estimation based on reliability and environment-operational conditions is a method to improve supportability. This method can guarantee non-delay in spare parts logistics and improve production output (Ghodrati, Banjevic, & Jardine, 2010).

1.2.3 Value-based optimization of replacement intervals

Growing business performance targets can be addressed by using reliability models. From the maintenance excellence viewpoint, the optimization of asset replacement and resource requirements decisions is essential for the continuous improvement (Jardine & Tsang, 2006). This becomes even more decisive in the case of asset intensive industries –such as Mining, Aeronautic, Defense, or Nuclear industries– with high investment equipment to perform operations. The constant pressure to reduce costs and increase utilization often leads to a stress on equipment, affecting reliability and throughput (Godoy et al., 2013). Hence, the interest lies in improving the system reliability. The operation of essential equipment is supported by critical components (Louit, 2007). Consequently, reliability enhancement of complex equipment can be achieved by preventive replacement of its critical components (Jardine & Tsang, 2006). Critical major components are often expensive and need high reliability standards, they are habitually related to extended lead times and influence on production and safety (Godoy et al., 2013). They are often related to lengthy plant shutdowns with associated production losses. These expected losses have a significant impact on tactical, financial, and logistic considerations. As a mitigation measure to this impact, critical components are monitored by using Condition-based Maintenance (CBM) (Godoy et al., 2013). Examples of these items in the mining industry are: mill liners, shovel swing transmissions, and haul truck engines. The challenge is to identify an optimal change-out epoch to intervene in major critical components in order to meet both reliability constraints and business goals.

Business-market conditions have the potential to change major components optimisation decisions. Replacement optimisation criteria depend on objectives that firms attempt to achieve. Internal scheduling principles, such as cost or availability, are traditionally preferred for setting maintenance intervention policies. Cost minimisation is based on the assumption to balance both replacement and operating costs (Jardine & Tsang, 2006). In turn, availability maximization (or downtime minimization) is in search of a balance between preventive replacement downtime and failure replacement downtime (Campbell et al., 2011). Using this kind of criteria, an optimal components overhaul and replacement policy can be properly defined to accomplish internal performance targets. Nevertheless, these widely-used practices do not usually consider relevant external factors, such as current business scenario at replacement epoch. Commodities price is an example of these external conditions in asset intensive industries. Different commodity prices (e.g. copper) may postpone or accelerate cost-based replacement decisions. If a favourable-price scenario is faced, then it could be more profitable to delay the intervention epoch and continue operating.

Relevant assumptions and limitations of the model are the following:

- It is not intended to provide a perfect forecast of copper prices, but rather the objective as value-adding is to include other relevant decision factors in addition to traditional cost minimization.

- Value creation can be considered as the difference between free cash flow and capital employed multiplied by the weighted average cost of capital (Adams, 2002).

- Short-term models are not suitable for the kind of components of this work. Major intervention intervals are set by several months or even years, and associated shutdowns by weeks.

As the idea is to facilitate the model applicability, a simpler but reasonable moving average method was used. Mean squared errors from moving average were sufficiently close to more advanced methods, such as exponential and logistic autoregressive models (ESTAR and LSTAR) or first-order autoregressive process AR(1). See Engel and Valdés (2002) for a further explanation of these methods on copper price forecasts.

1.2.4 Optimizing maintenance service contracts under imperfect maintenance and a finite time horizon

Coordination in the supply chain, *i.e.* channel coordination, plays a relevant role on outsourcing. In the current dynamic environment, coordination of the parties is essential for services in the chain. Kumar (2001) suggests that two types of coordination are necessary in supply chain management: horizontal coordination (between the players who belong to the related industry) and vertical coordination (across industry and companies). Although the need for coordination is becoming increasingly evident, efforts to create infrastructures to enact such coordination are still in their early stages. Kumar (2001) states that supply chains can create systems that integrate instant visibility and whole dynamic supply chains on an as-needed basis. Those chains are more likely to reach competitive advantages over those that do not adopt such systems.

There are several methods to achieve cooperation among a client and a contractor. A common practice is to use a *work package contract* which specifies a maintenance strategy and a cost structure that leads the contractor to accept the deal. This kind of contract falls into the category of *labor plus parts*, in which the contractor sees no incentives to improve its performance (Tarakci, Tang, Moskowitz, & Plante, 2006a), as the more its services are required, the more the contractor earns. For the contractor, the usual focus is to keep customer loyalty by showing capability to outperform competitors (Egemen & Mohamed, 2006).

Another aspect to take into account when negotiating contracts is the system level at which the contract acts on a system. The contract may include the maintenance of (usually) a single component of a complex system and can also be an umbrella or full service contract considering the whole system. An example of the first case is presented by Tarakci et al. (2006a). The same authors study a manufacturing system with multiple processes where each component is maintained independently (Tarakci, Tang, Moskowitz, & Plante, 2006b).

Considering the need for reaching effective coordination of the supply chain, Tarakci et al. (2006a) study incentives to maximize the total profit of the service chain. Namely, contracts which aims to achieve a win-win coordination to maximize the profits of the actors. According to Tarakci et al. (2006a), these contracts lead the contractor to improve the performance of maintenance operations. They demonstrate that this kind of contracts can be an effective tool to achieve the desired overall coordination. Nevertheless, they consider both perfect maintenance for preventive actions and infinite horizon contracts. These two limitations do not seem to make a realistic condition for a full implementation of the model in the operational reality.

The inclusion of imperfect maintenance contributes to a realistic modeling of system failure rates. Changes in failure patterns strongly influence maintenance and replacement decisions (Pascual & Ortega, 2006). Perfect maintenance contemplates that every maintenance action returns the system to its“as good as new” condition. However, Malik (1979) points out that working systems under wear-out failures are not expected to be restored to a new condition, and proposes the inclusion of a maintenance improvement factor for imperfect repairs. Furthermore, Nakagawa (1979) suggests that failure rate functions on imperfect maintenance cases could be adjusted using a probability approach; thus, the action is perfect “as good as new”) with probability (1-α) and minimal (“as bad as old”) with probability α. Zhang and Jardine (1998) argue that enhancements by overhauls tend to be magnified by Nakagawa’s model and there is a possibility that the failure rate could be bounded; consequently, the appropriateness of the model could be restrained. Zhang and Jardine present an optional approach in which the system failure rate function is in a dynamic modification between overhaul period, since this rate is considered between “as bad as old” and “as good as previous overhaul period” using a fixed degree. Zhang and Jardine’s approach is used in the model formulation of the present paper. Due to imperfect maintenance sets the system failure rate between a new condition and a previous to failure condition (Pham & Wang, 1996), the incorporation of this realistic assumption is fundamental for model applicability.

An important aspect that should be considered during the coordination process is the time-horizon of the contracts. This condition does not only hold because the amortization of investments by the provider but also because the assets under consideration suffer in general an aging process that increases the need to perform maintenance and overhaul actions. Regarding this, Lugtigheid, Jardine, and Jiang (2007) focus on finite-horizon service contracts. They note the lack of literature for finite-horizon contracts, and present several methods and consider repair/replacement for critical components. In our case, the focus is not on component level, but on system level. Complementarily, Nakagawa and Mizutani (2009) propose finite-interval versions for classic replacement models, such as models of periodic replacement with minimal repair, block replacement and simple replacement. Regarding the aging process is often an effect of imperfect maintenance practices that can be modeled using different approaches, many of them described in references such as Wang (2002); Li and Shaked (2003); Nicolai and Dekker (2008). Nakagawa (1979) also consider imperfect maintenance models but do not split costs into in-house and outsourcing costs. In this article we focus on the well known method described by Zhang and Jardine (1998), but the application of the concepts to other approaches like virtual age models (Kijima, 1989) is straightforward.

1.2.5 A decision-making framework to integrate maintenance contract conditions with critical spares management

As an interesting strategy to achieve cost-benefits, consolidating inventory locations by cooperative pooling has been addressed by Kilpi and Vepsäläinen (2004); Lee (1987); Dada (1992); Benjaafar, Cooper, and Kim (2005), among other studies. In the context of repairable spares pooling, the cost allocation problem is analyzed using game theoretic models by Wong, Oudheusden, and Cattrysse (2007). As recent implementations, a virtual pooled inventory by managing information systems is included in Braglia and Frosolini (2013) and a calculation model of spare parts demand, storage and purchase planning in the coal mining industry is reported by Qing he, Yan hui, Zong qing, and Qing wen (2011). When dealing with cooperation in contractual alliances, the study of Gulati (1995) states the relevance of interfirm trust to deter opportunistic behaviour in a shared ownership structure. Such trust is an important issue related to pooling strategies. A widely applied modeling for repairable items stockholding focused on system availability and spares investment is provided by Sherbrooke (2004). Since its accuracy to determine the optimal inventory levels for both single-site and multi-echelon techniques, the above-mentioned model is used to adapt the concept of spare service level in the present paper.

Maintenance outsourcing under supply chain coordination is discussed by Tarakci et al. (2006a), a study that deals with incentive contracts terms to coordinate agents and clients by a maintenance policy seeking to optimize the total profit. The work of Pascual, Godoy, and Figueroa (2012) extends this approach by incorporating realistic conditions, such as imperfect maintenance and finite time-span contract . That model adapts the failure rate by using the system improvement model of Zhang and Jardine (1998). Such concepts of profitable coordination and imperfect maintenance are also used in the present paper to improve the practical applicability for asset intensive operations.

There are studies that specifically deal with allocation spare parts in service contracts. A paper intending to incorporate repair contract selection and spares provisioning under a multicriteria approach is presented in Teixeira de Almeida (2001). In Nowicki, Kumar, Steudel, and Verma (2008), a profit-centric model is presented for spares provisioning under a logistics contract for multi-item and multi-echelon scenario. In Mirzahosseinian and Piplani (2011), an inventory model is developed for a repairable parts system by varying failure and repair rates. A dynamic stocking policy to replenish the inventory to meet the time-varying spare parts demand is proposed by Jin and Tian (2012). A reliability-based maintenance strategy required for the spares inventory is described in Kurniati and Yeh (2013), although its scope does not cover contract conditions. Since the relevant effect of warranties as service contracting, a three-partite stochastic model including client, agent, and customer is presented in Gamchi, Esmaeili, and Monfared (2013). However, none of these works has faced the pool management problem by using the realistic assumptions of imperfect maintenance, finite contract duration, or profitable channel coordination.

Regardless of the extensive literature, the present paper introduces new contributions in terms of formulation and analytical properties. To the best of our knowledge, a model capable of delivering profitable decisions to allocate the pool of critical spare parts within maintenance outsourcing contracts –via the inclusion of imperfect maintenance and the optimal conditions for supply chain coordination– has not been addressed in the literature.

1.3 Thesis Structure

The methodology is illustrated by a sequential achievement of the objectives of each paper appended to this thesis, as follows. **Paper I** aims to select systems and components to be studied by ranking their criticality. It proposes a user-friendly graphical technique in order to handle the prioritization problem in production lines with intermediate buffers. This technique has been called the *System Efficiency Influence Diagram* (SEID). After prioritizing the most important spare components, **Paper II** attempts to orient the time decision to balance critical spare parts ordering with continuation of operation. It presents a graphic technique which considers a rule decision based on both condition-based reliability function and stochastic/fixed lead time. This performance indicator has been called *Condition-Based Service Level* (CBSL). Another question of interest is when to replace, **Paper III** guides the decision about the best epoch to intervene in major critical components. It is considered the maximization of business value, rather than simple minimization of cost. Condition-based maintenance is also used in the estimation of conditional reliability across the study period. A next step under the PAM perspective is to balance in-house critical resources with outsourcing services, **Paper IV** determines contractual conditions to coordinate the supply chain through a preventive maintenance strategy. This maximizes the total expected profit for both contractor and customer, under imperfect maintenance and a finite time-span contract. Finally, an interesting closure of the thesis is to integrate such maintenance contracting terms with spares supply practices. **Paper V** efficiently integrates contractual conditions with critical spares stockholding. An original joint value – preventive maintenance interval and spares stock level– sets the optimal agreement to profitably allocate the pool of components within the service contract.

The results obtained from **Paper I** to **Paper V** allow integrating the models developed into a general decision support system for critical spare parts under an asset management perspective. This general structure is indicated in Figure 1-2. The research, models, and decision tools involved are presented in the following sections.

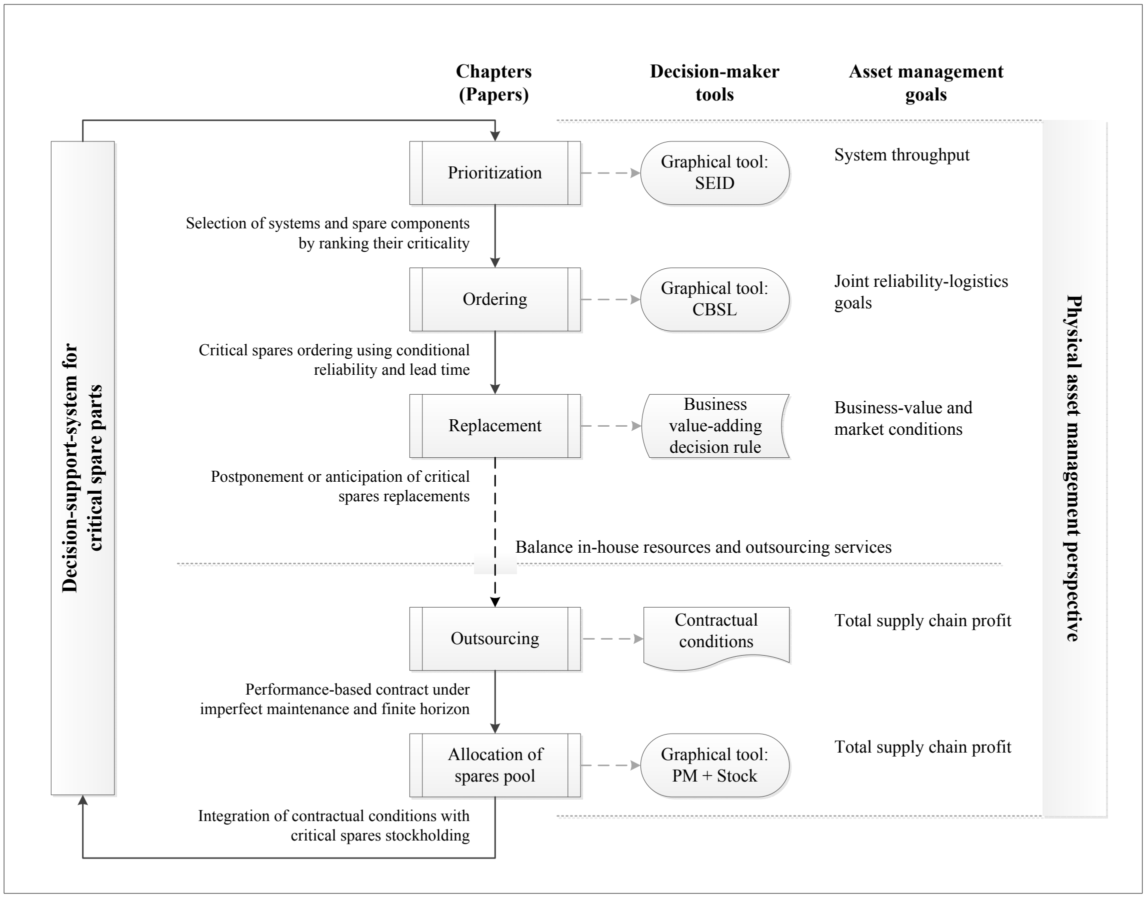

Figure 1-2: Thesis structure given by the five papers under asset management

2. THROUGHPUT CENTERED PRIORITIZATION IN THE PRESENCE OF BUFFERS: THE SYSTEM EFFICIENCY INFLUENCE DIAGRAM

The key is not to prioritize what is on your schedule, but to schedule your priorities.
— Stephen Covey

To meet the increasing challenges of current industrial environment, organizations must continuously enhance their capability to add value and improve the cost-effectiveness of their decision processes. These include the selection of those systems (machines) and actions that may render the highest overall savings with the lowest efforts, and then, set their associated lifecycle policy resolutions. Setting such policies requires resources. As these resources are usually scarce and the number of machines is usually high, a systematic prioritization process must be established (Pascual, Del Castillo, et al., 2009) and a proper decision aid tool must be selected.

Pareto analysis has been commonly used to select the components and most critical failure modes of a system. A limitation of this approach is that it uses a single criterion to prioritize. In maintenance management, availability is a typical indicator. This indicator does not allow to ensure whether the cause of failure is a high frequency (reliability) or long downtime (maintainability). To help overcome this problem, Labib (1998) suggests the *Decision Making Grid*. It uses a diagram that includes frequency and downtime, allowing the monitoring of equipment and indicating the appropriate action. An example of a non-graphical technique is the *Analytic Hierarchy Process*, which uses pairwise comparisons and relies on the judgements of experts to derive priority scales (Saaty, 2008). A disadvantage of using this method is that in situations with a sizeable number of alternatives, the required comparison step can be unwieldy and excessive resource consuming. In the case of *Failure Mode and Effect Analysis* (FMEA), the rating to calculate the priority of the failures is called *risk priority number* (Franceschini & Galetto, 2001), *severity* (Pasquini et al., 2011) and/or *criticality rank* (Selvik & Aven, 2011), which is worked out by the product of different ratings: frequency, consequence, detectability, etc. Nonetheless, in many cases the estimation of these factors can be highly subjective. A more advanced technique is proposed by Knights (2004) through the *Jack Knife Diagram* (JKD), a logarithmic scatter plot that involves simultaneously three performance indicators: frequency, downtime, and unavailability. Using JKD, it is possible to classify failures as acute and/or chronic. Acute failures indicate problems in inspections, resource availability, preventive maintenance, among others. Furthermore, chronic failures indicate problems in equipment operation and materials quality. The JKD technique only considers time based information, excluding economic effects which certainly affect prioritization in a business context. In order to surpass this limitation, Pascual, Del Castillo, et al. (2009) propose the *Cost Scatter Diagram* (CSD) that incorporates the economic dimension and includes JKD analysis as a special case. This technique explores the opportunities for improvement using business-oriented performance indicators, such as: total costs, direct costs, availability, frequency, and downtime. None of the aforementioned tools explicitly consider that in production systems there exist elements that mitigate the impact upon the occurrence of unanticipated events (i.e. failures), and even expected (scheduled maintenance). These elements range from stockpiles (buffers), redundant equipment, availability of *in situ* spare parts, to insurance against all risks, to mention some of them.

A production line may have none, one, or many intermediate buffers. If any of the machines of the line fails, the buffers can eliminate/mitigate the idleness that produces the flow discontinuity, enhancing the production rate. While larger buffers can absorb longer interruptions, they also increase inventory costs (Burman et al., 1998). This observation justifies inventory reduction strategies such as the well-known *Just in Time* (Shah & Ward, 2003). As the interruption in production flows may generate costly consequences, the reduced presence of buffers in plants has created the need to continuously improve maintenance strategies (and priority setting needs) (Crespo & Gupta, 2006).

In the context of decision making for production systems, there is a relevant difference between maintenance management and physical asset management. According to PAS-55 (British Standards Institution, 2008), asset management is defined as: *systematic and coordinated activities and practices through which an organization optimally manages its assets, and their associated performance, risks and expenditures over their lifecycle for the purpose of achieving its organizational strategic plan*. In maintenance management, a common performance indicator is machine availability. Although it may seem suitable that the maintenance function keep focus on improving the equipment availability, it may also lead to reduced care on production efficiency and to a biased business vision. Asset management avoids to optimize indices separately, and advices applying a global perspective considering the implications of maintenance policies within the organization strategic plan (Crespo et al., 2003). According to Li et al. (2009), throughput is relevant for the design, operation and management of production systems, because it measures the system production volume and represents the line efficiency. Then, a key performance indicator for asset managers may be the system throughput or, complementarily, the production efficiency. The latter sets a need to characterize the system efficiency, and thus to provide a systems engineering management perspective. Simulation based efficiency estimation provides a guide for incorporating realistic conditions to evaluate system level improvements. As example, Murino et al. (2009) use simulation to consider effect of condition based maintenance. However, time, cost and expertise required to develop simulation models may impose a barrier for their application in industry (Kortelainen et al., 2000; Louit, 2007; Murino et al., 2009). Analytical modeling may offer a simpler and cheaper alternative to simulation. One example is the DDX method (Dallery et al., 1989), which considers transfer lines with unreliable machines and finite buffers. In the case of a homogeneous line, the behavior is approximated by a continuous flow model and decomposing the system into sets of two-machine lines (for which closed solution exist). The decomposition results in a simple and fast algorithm which provides performance indicators, such as expected throughput and buffer levels. Experimental results have shown that this approximate technique is very accurate. In the case of a non-homogeneous line, a simple method is introduced to transform it into a homogeneous line. In addition to DDX, there exist a number of analytical models to estimate the system throughput. A review of these methods can be found in Li et al. (2009).

To handle the prioritization problem in production lines this paper proposes the System Efficiency Influence Diagram (SEID). Its associated performance indicator is the expected system throughput. To illustrate its significance, three case studies are presented. The efficiency estimation is performed in our cases using the DDX method, which allows the estimation of the so-called influence factors. SEID may also be implemented using other throughput estimation models, including simulation.

Through the use of prioritization tools already mentioned, maintainers can make decisions about maintenance policies. However, such tools consider only an equipment level criterion (individual machine availability). Maintainers can use SEID to prioritize and make decisions about maintenance policies to be used too, but with a system criterion, namely considering the system throughput. On the other hand, a designer can use SEID to set the capacities of the buffers, knowing how each machine influences the line efficiency due to the presence of such buffers. Asset managers may also be interested in increasing the system efficiency to achieve the production goals of the company. SEID may give them an accurate prioritization criterion to analyze ways to increase throughput consequently.

Having introduced the importance of the proposed decision aid tool in the context of prioritization and system efficiency, the rest of the chapter is organized as follows: Section 2.1 presents the SEID. Section 2.2 describes the case studies, the numerical case of a production line of four equipments, the case of a real line of vehicle assembly, and the real case of a production line in a mining operation. Finally, Section 2.3 reveals the conclusions of the work.

2.1 SEID Technique

A line with k machines in series is considered. If all machines operate, the system throughput is λ_p (production units per unit time). The first machine is never starved (always has raw material available) and the last is never blocked (can work continuously because it is never obstructed due to downtime of downstream machines or saturation of the downstream buffer). The failure rate (the inverse of the mean time to fail) of machine i is λ_i, and its repair rate is μ_i, $i = 1, ..., k$. We define the unavailability factor as

$$D_i = \frac{\lambda_i}{\mu_i}, \quad i = 1...k. \tag{2.1}$$

From Buzacott and Hanifin (1978), the expected efficiency (produced units/planned units, when no failures occur) of a system without buffers (η_0) is

$$\eta_0 = \frac{1}{1 + \sum_{i=1}^{k} D_i}. \tag{2.2}$$

On the other hand, Buzacott (1967) states that the system efficiency with infinite buffers (η_∞) should be limited by the least efficient machine, as follows

$$\eta_\infty = \min\{\eta_i\}, \quad i = 1...k, \tag{2.3}$$

where $\eta_i = \frac{1}{1+D_i}$. Therefore, the system efficiency η with finite buffers must be between the limits: $\eta_0 \leq \eta \leq \eta_\infty$.

The presence of buffers and their associated capacity do affect the system efficiency. For priority setting purposes, we propose to use an equivalent system without buffers, similar to Equation (2.2), but adding system influence factors $\rho_i, i = 1...k$ to take into account the presence of buffers. Hence, the following metamodel constitutes the basis for SEID

$$\eta(\mathbf{d}_0) = \frac{1}{1 + \sum_{i=1}^{k} \rho_i(\boldsymbol{d}_0) D_i}, \tag{2.4}$$

where $\mathbf{d}_0$ is the configuration vector defined by the equipment parameters and the capacities c_i of current buffers in a system, namely: $\mathbf{d}_0 = \{\lambda_1, \mu_1, c_1, ..., c_{k-1}, \lambda_k, \mu_k\}$.

To estimate the influence parameters, the original system is perturbed and the efficiency is estimated. This generates a linear system of equations based on

$$\mathbf{Ax} = \mathbf{b}, \tag{2.5}$$

where $\mathbf{A}$ is the matrix formed by unavailability factors D_i (D^*_{ij} indicates the perturbed unavailability factor), $\mathbf{x}$ is the unknown vector with the influence parameters, and $\mathbf{b}$ the vector that is derived from SEID metamodel. Then, the estimation of $\boldsymbol{\rho}$ is given by the resolution of

$$\begin{bmatrix} D_{11} & D_{12} & D_{13} & \cdots & D_{1k} \\ D^*_{21} & D_{22} & D_{23} & \cdots & D_{2k} \\ D_{31} & D^*_{32} & D_{33} & \cdots & D_{3k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ D_{k1} & D_{k2} & D_{k3} & D^*_{k-1k-1} & D_{kk} \end{bmatrix} \begin{Bmatrix} \boldsymbol{\rho}_1 \\ \boldsymbol{\rho}_2 \\ \boldsymbol{\rho}_3 \\ \vdots \\ \boldsymbol{\rho}_k \end{Bmatrix} = \begin{pmatrix} \frac{1}{\eta_1} - 1 \\ \frac{1}{\eta_2} - 1 \\ \frac{1}{\eta_3} - 1 \\ \vdots \\ \frac{1}{\eta_k} - 1 \end{pmatrix}.$$

From observation of Equation (2.4), when $\rho_i D_i$ is relatively large, the effect of the i-th machine on the system efficiency is greater with respect to other machines. While D_i only depends on the i-th machine, ρ_i depends on the system configuration vector $\boldsymbol{d}_0$. This allows defining a scatter diagram, where one axis is the unavailability factor D_i of each machine when working alone, while the other axis is its system efficiency influence factor (ρ_i) given the current system design configuration ($\boldsymbol{d}_0$). Figure 2-1 shows an example of this technique for a 3-machine system. Each hyperbola represents an iso-influence line on the system expected throughput. Applying a

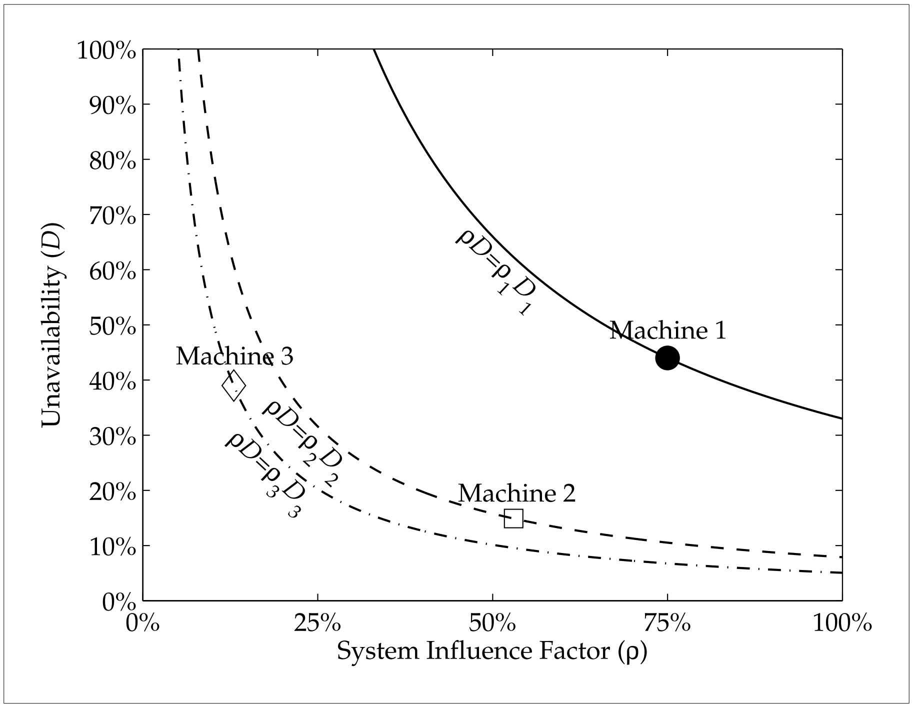

Figure 2-1: SEID using linear scales

logarithmic scale to the axes, they are displayed as linear isoquants, facilitating the analysis. This new graph with bi-logarithmic axes is shown in Figure 2-2, which has been selected to make the analysis using the SEID technique.

As aforementioned, the largest ρD products set the order of priority for the machines. In the case of Figure 2-2, the descending order would be: 1, 2, and 3. Machine 3 has a higher unavailability factor compared to machine 2, but $\rho_2 D_2$ is higher than $\rho_3 D_3$. From the standpoint of system throughput, machine 3 is the less relevant. Figure 2-2 has been divided into four quadrants. To set the axes, we have used, arbitrarily, the mean values of machine unavailability factors and system efficiency influence factors respectively. In quadrant IV there are machines with a higher system efficiency influence factor, and in quadrant II are positioned those having a higher unavailability factor. However, the quadrant I is the most critical to prioritize according to system efficiency throughput, because it concentrates all

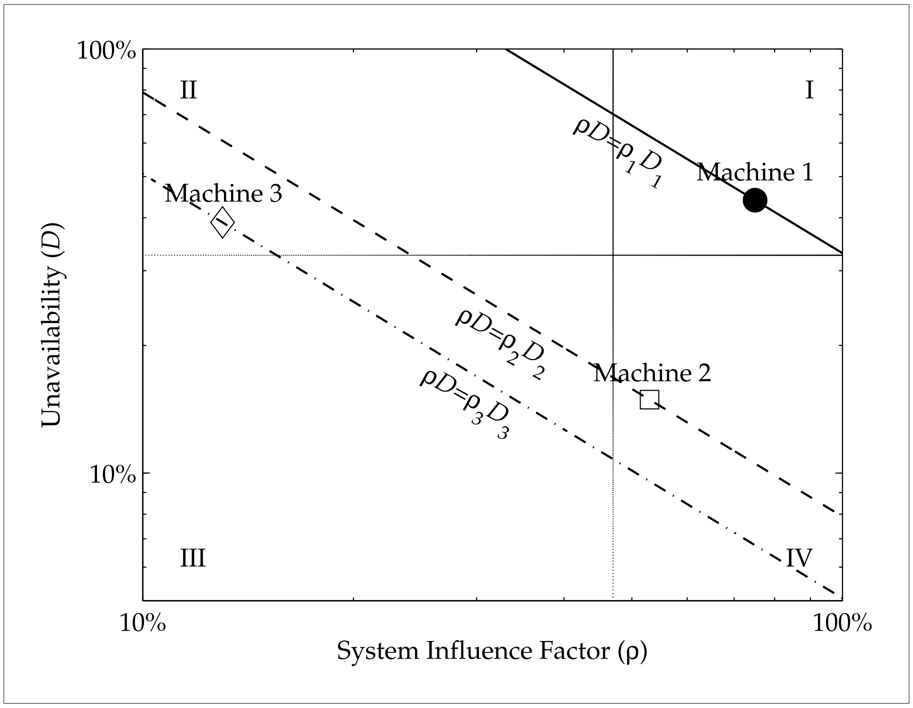

Figure 2-2: SEID with bi-logarithmic axes

machines having both high unavailability factor and large system system efficiency influence factor. In this quadrant the ρD isoquants with higher value are located. In the same way, in quadrant III are ρD isoquants that may be regarded less critical for system efficiency. Figure 2-3 shows an example of how the SEID metamodel fits well in a 2-machine system. It is composed of a crushing plant, a milling plant, and an intermediate stock pile (Madariaga & Pascual, 2009). From Figure 2-3, it is possible to deduce that ρ factor behaves in an accurate way around real data provided by the case. The estimated efficiency using SEID technique is very close to the one calculated using the model, which may be analytical –such as DDX– or simulation-based.

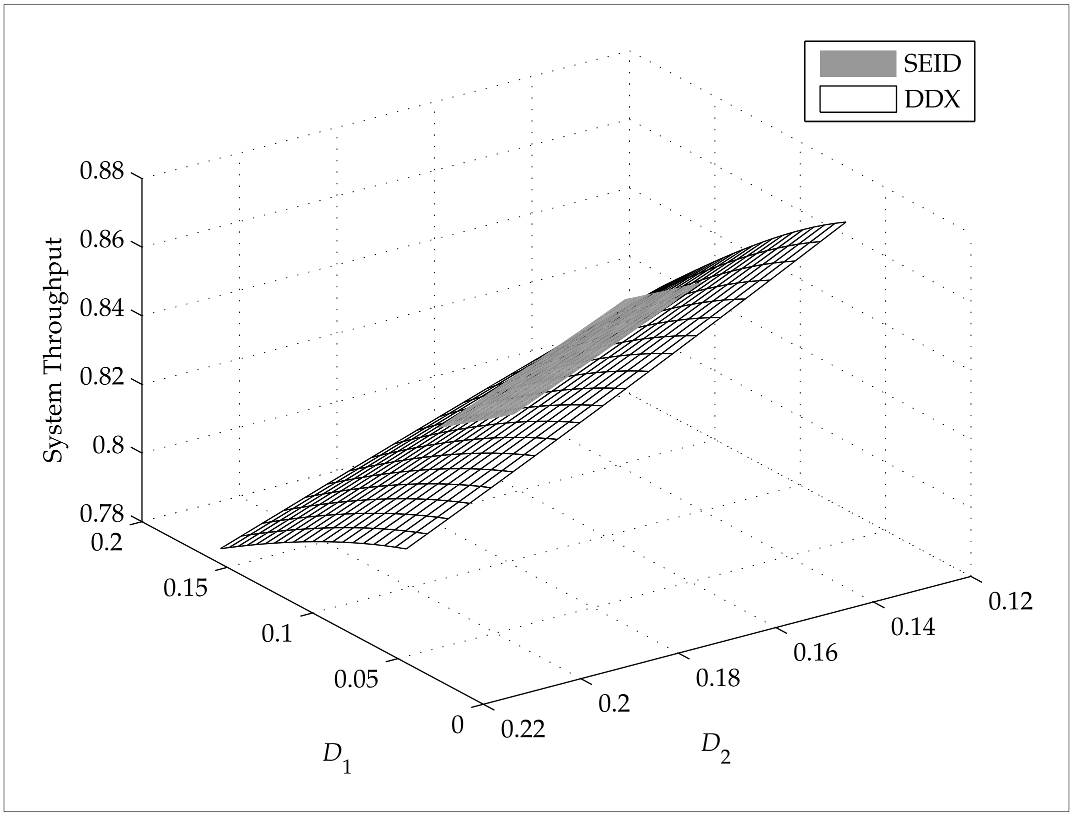

Figure 2-3: Comparison of system throughput estimation between SEID technique and DDX model

2.2 Case Studies

Three case studies illustrate the benefits of using SEID. The first study is a numerical case of a four-machines production line using data from an example given by Dallery et al. (1989), which illustrates the significant differences in analysis obtained compared with JKD. To demonstrate practical experience of applying SEID, the second case considers a vehicle assembly line, described in Tempelmeier (2003). Finally, the third study is based on a real case described by Madariaga and Pascual (2009), which shows a conveyor system within a mining operation in Chile.

Table 2-1: Parameters of case study 1. λ_p = 1

Machine	Failure rate (h^{-1})	Repair rate (h^{-1})	Buffer capacity
1	0.04	0.08	20
2	0.02	0.04	0
3	0.03	0.06	20
4	0.02	0.04	-

2.2.1 Case Study 1. Four-machines transfer line

Table 2-1 lists the parameters of a numerical case taken from Dallery et al. (1989). JKD (Figure 2-4) for this case shows that unavailability factor is identical for all four machines, so they share the same unavailability factor isoquant. JKD does not allow priority setting based on machine availability. The analyst using JKD would have to choose machine reliability (frequency) or machine maintainability (downtime) as priority setting criterion. SEID (Figure 2-5) shows better results as it is able to discriminate among the machines. Priorities in descending order are: 2, 3, 4, and 1 respectively.

To check SEID consistency, we also ranked machines by observing the change in efficiency when perturbing the unavailability factor of each machine separately by 10% with respect to the reference configuration (Table 2-2). Machine rankings are the same for both methods. As an advantage, SEID graphically discriminates which factor (unavailability or system influence) is the dominant to explain the importance of a given machine on the expected throughput.

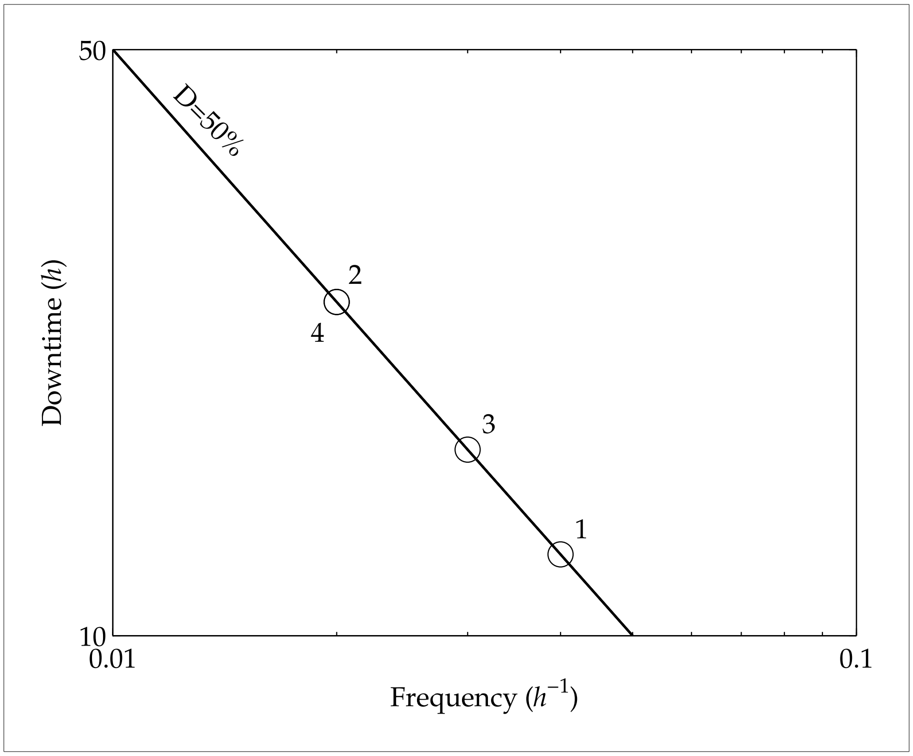

Figure 2-4: JKD using case study 1

Table 2-2: Comparison of priorities using DDX and SEID

Machine	$\Delta\eta$	DDX order	SEID order
1	0.0034	4	4
2	0.0074	1	1
3	0.0071	2	2
4	0.0042	3	3

2.2.2 Case Study 2. Vehicle assembly line

Table 2-3 shows an adapted version of a case described by Tempelmeier (2003), and lists the parameters of a production line of 19 machines with intermediate buffers. JKD analysis (Figure 2-6) indicates that the most critical machines for prioritization

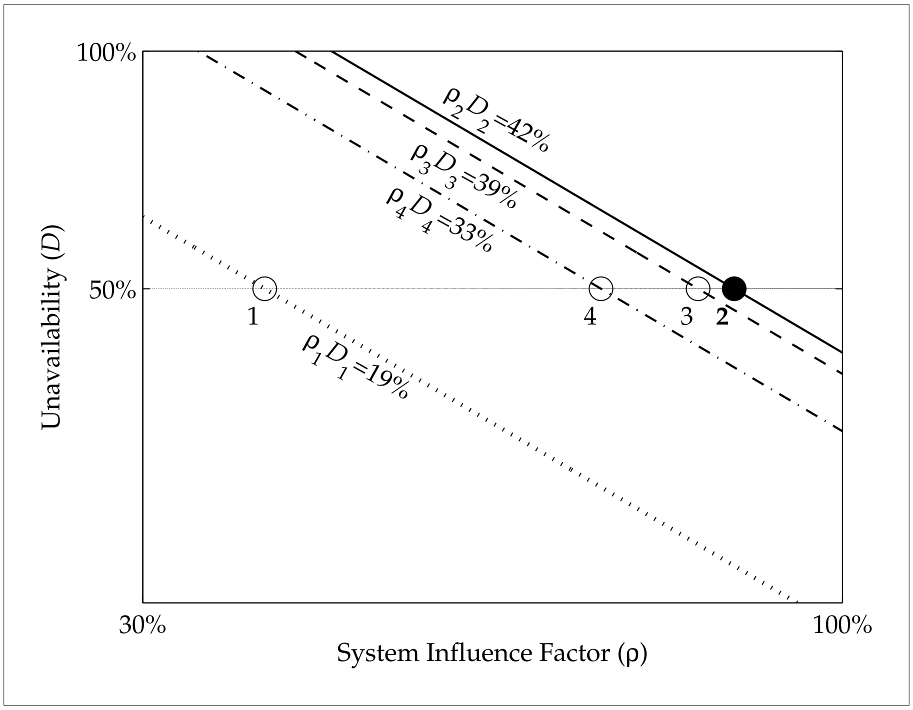

Figure 2-5: SEID using case study 1

are: 9, and 13 or 8 equally in the second and third. We also used this case to show a three dimensional version of SEID (Figure 2-7). On the horizontal plane may be observed the axes that build a similar graph to JKD (downtime and frequency), but additionally Figure 2-7 shows the influence factors on the vertical axis. In this format, JKD is a special case of SEID.

Similar to the previous case, there are machines with higher associated $\boldsymbol{\rho}$ (in this case, the machines: 7, 9, and 13), but as the focus is on system efficiency, Figure 2-8 shows SEID in its 2D version which is easier to interpret.

Table 2-3: Parameters of case study 2. $\lambda_p = 2.1$

Machine	Failure rate (min^{-1})	Repair rate (min^{-1})	Buffer capacity
1	0.000459	0.020	14
2	0.000498	0.024	9
3	0.000296	0.018	9
4	0.000252	0.036	16
5	0.000346	0.021	28
6	0.000841	0.036	23
7	0.000194	0.015	27
8	0.000884	0.029	8
9	0.000794	0.023	12
10	0.000122	0.030	28
11	0.000084	0.028	6
12	0.000130	0.032	9
13	0.000515	0.017	12
14	0.000311	0.026	8
15	0.000675	0.026	24
16	0.000232	0.021	29
17	0.000412	0.021	10
18	0.000147	0.018	13
19	0.000621	0.023	-

Comparing Figures 2-6 and 2-8 respectively, although the machines 9, 13, and 8 remain the most critical for the system throughput, there are machines which are at the top of prioritization according JKD analysis, but from the focus of efficiency they are less important. An example of this priority difference is machine 2. It has a

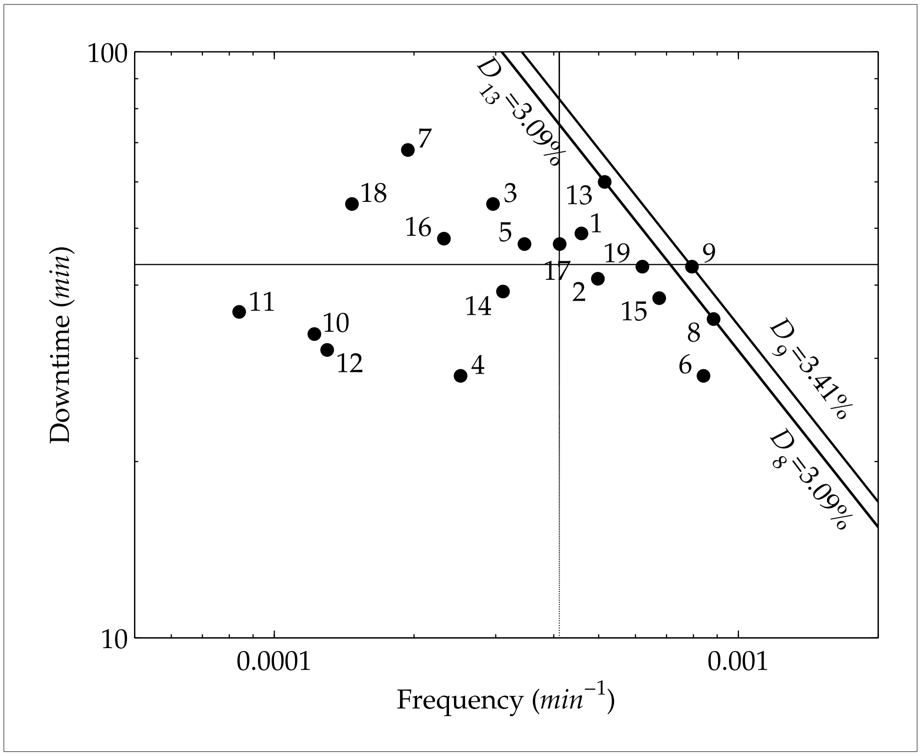

Figure 2-6: JKD using case study 2

high unavailability factor but a medium influence factor. Some machines rank higher if we consider throughput as priority setting indicator.

Regardless of the existence of some overlap of a critical priority for the present case between the JKD and SEID, the main difference is SEID gives a completely different approach to prioritization than JKD. The focus is no longer centered on a machine perspective, but on a systemic one.

2.2.3 Case Study 3. Mining conveyor system

Table 2-4 shows the parameters of a real line with 11 machines, with three intermediate stockpiles, associated to a copper mining operation in northern Chile (Madariaga & Pascual, 2009). SEID is shown in Figure 2-9. We observe two clusters

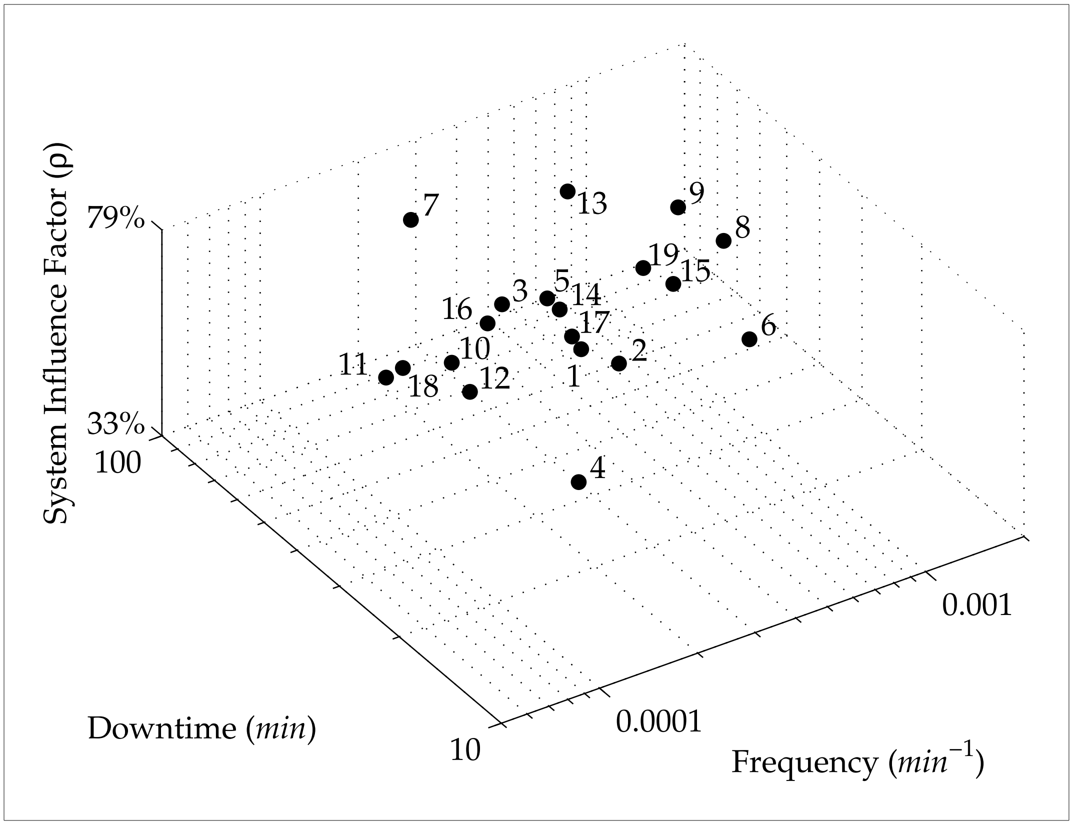

Figure 2-7: SEID 3D on the vertical axis shows the system influence factors of case study 2

with respect to the influence parameters. Again, machines with similar levels of unavailability factors such as 2 and 6 highly differ in its importance of efficiency due to the existing buffer configuration. Note that machine 6 is surrounded by buffers. It is not the case of machine 2.

2.3 Conclusions

The work proposes a graphical technique for decision-making to prioritize equipments according to their effect on the expected system efficiency and taking into account intermediate buffers. SEID represents an effective tool to quantitatively show how system efficiency is more interesting from a business perspective than

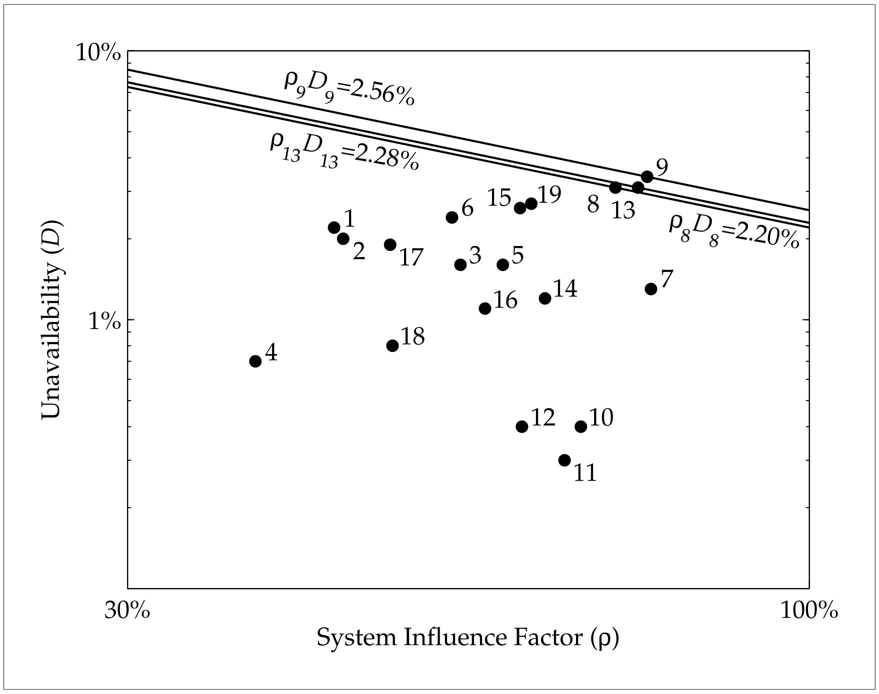

Figure 2-8: SEID using case study 2

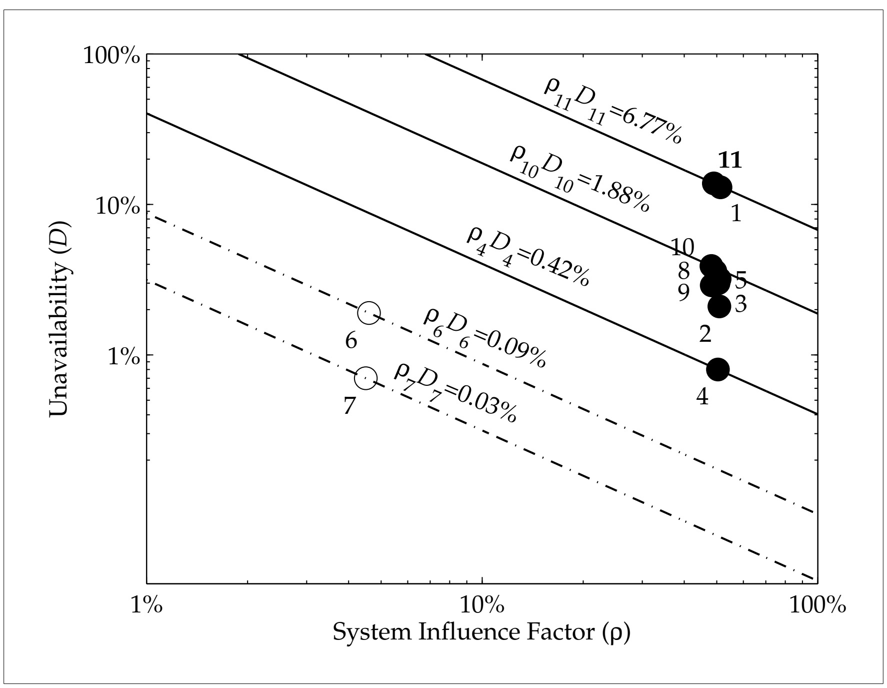

Figure 2-9: SEID using case study 3

Table 2-4: Parameters of case study 3. λ_p = 4.0

Machine	MTBF (h)	MTTR (h)	Buffer capacity (kton)
1	2.07	0.27	0
2	34.48	0.72	0
3	12.66	0.38	0
4	47.62	0.40	0
5	20.83	0.66	15
6	55.56	1.04	15
7	142.86	0.97	15
8	33.33	1.19	0
9	27.03	0.78	0
10	19.23	0.75	0
11	10.87	1.50	-

machine availability. The grounds for the SEID development are the assumptions of Markovian processes for both the failure and the repair rates. The proposed tool avoids prioritizing using equipment level tools, such as JKD or CSD, or setting priorities only with capital investments as selection criterion. Due to the existence of buffers, it is possible that relatively low investment equipment or machines with relatively high availability are the most critical for the system throughput. SEID highlights how machines with higher inherent unavailability factors are not necessarily the most relevant for efficiency. The technique can be used by asset managers to make decisions about maintenance policies and redesign buffer capacities. As future development, the SEID technique can be extended in order to be used with general distributions for both the failure and repair processes.

2.4 Acknowledgements

The authors wish to acknowledge the partial financial support of this study by the FOndo Nacional de DEsarrollo Científico Y Tecnológico (FONDECYT) of the Chilean Government (1090079).

3. CRITICAL SPARE PARTS ORDERING DECISIONS USING CONDITIONAL RELIABILITY AND STOCHASTIC LEAD TIME

A fair request should be followed by the deed in silence.
— Dante Alighieri

Decision-making processes are crucial for organizations within a scenario of intense competitiveness. Since companies are frequently required to reduce production costs and increase asset utilization, misguided decisions may lead to over-stress on equipment. This situation affects reliability and, more importantly, system throughput. Continuous improvement of the ability to add value and enhance profitability of operations is needed by firms in pursuit of performance excellence (Jardine & Tsang, 2006). An efficient resources ordering is indispensable to achieve significant availability exigencies of equipment-intensive industries, such as Mining, Aeronautic, Nuclear Energy, or Defense. This equipment is supported by spare parts inventories, which are particularly relevant considering the influence of stock-outs on downtime (Louit, 2007). Appropriate spare parts allocation decisions are therefore essential to system performance of these industries.

Spare parts play a fundamental role in the support of critical equipment. In a typical company, approximately one third of all assets corresponds to inventories (Díaz & Fu, 1997). Of these assets, critical spare parts have special relevance because they are associated with both significant investment and high reliability requirements. As an example, spares inventories sum up above US$ 50 billion in the airlines business (Kilpi & Vepsäläinen, 2004). The mismanagement of spare parts that support critical equipment conduces to considerable impacts on financial structure and severe consequences on operational continuity. The improvement of key profits on both logistics and maintenance performance can be achieved by inventory management of costly components, which have extremely criticality on equipment-intensive industries (Braglia & Frosolini, 2013). Therefore, efficient decisions about spare-stocking policies can become essential in the cost structure of companies. In order to provide an efficient spare management performance, a suitable ordering strategy can be relevant. A spare part classification scheme becomes necessary to set optimal policies for those spares that may affect the system the most, and at the least effort. We proposed an ordering decision-aid method to secure the spare management performance into an operational environment that needs continuity to compete into a demanding business context.

3.1 Critical Spare Parts and Maintenance Strategy

The need for spare parts inventories is dictated by maintenance actions (Kennedy et al., 2002). In addition, maintenance strategy can be treated by Condition-Based Maintenance (CBM). In this case, models incorporate information about equipment conditions in order to estimate the conditional reliability. This information comes from, for instance, vibrations measurements, oil analysis, sensors data, operating conditions, among others. These measures are called covariates. Covariates may be included on the conditional reliability using the Proportional Hazards Model (PHM) (Cox, 1972), which allows combining age and environmental conditions. In the interaction between operational environment and equipment, while age can be relatively easy to notice, deterioration can be measured by conditions assessment (Amari et al., 2006). Therefore, CBM becomes useful to set maintenance policies even with different levels of monitoring restrictions. Compared to usual time-based maintenance strategies, condition monitoring systems offer significant potential to add economic value to spares management performance (Van Horenbeek et al., 2013). Particularly, this paper uses CBM models to calculate conditional reliability in order to make ordering or replacement decisions.

Lead time is another important aspect to consider in spare parts ordering. The random time between fault event and the actual component failure may cause system performance deteriorations (Das & Acharya, 2004). Nonetheless, it also provides a opportunity window to set replacement policies. Logistically, there are also delays between the order of spares and their arrival (Wang et al., 2009). This situation is even more crucial when spare parts are critical, since they are not always available at the supplier store. Customs delays and the need of special transport are a source of significant lead times; moreover, when dealing with complex equipment parts made to order, lead times may exceed a year (Van Jaarsveld & Dekker, 2011). The lack of these items because of a delay in delivery (and their consequent installation) may have severe consequences in the operational continuity.

The core of this paper is on those critical spare parts that affect production, safety, are expensive, highly reliable, and usually are associated with higher lead times. These items are critical too, when they support equipment which is essential in an operational environment (Louit, 2007). Henceforward, all spare parts that meet these characteristics will be called, “Condition Managed Critical Spares”, or just CMS. CMS are repairable, however their repair times are slower than supplier lead times, this particularity turns these CMS into non-repairable spare parts for the purposes of this model. As CMS are not available in store, CMS condition is monitored as a mitigation measure to its criticality in the operation. Justification for not having them in store lies in the expectation that the CBM models will predict failures with sufficient lead time to overcome the need for spare-stocking.

Previous works have treated the decision-making process using CBM, for instance: research deals with a continuously deteriorating system which is inspected at random times sequentially chosen with the help of a maintenance scheduling function (Dieulle et al., 2003). There is also research obtaining an analytical model of the policy for stochastically deteriorating systems (Grall et al., 2002). However, spare parts issues are not included on those papers. Furthermore, there are several researches for CBM policies that consider unlimited spare parts which always are available (Amari & McLaughlin, 2004). Nevertheless, the focus of this paper is on critical spare parts which are, precisely, not available in store. According to (Wang et al., 2008), few existing ordering and replacement policies are proposed in the context of condition-based maintenance. In fact, the work described by Wang et al. (2008) aims to optimize CBM and spare order management jointly. Kawai (1983a) and Kawai (1983b) consider optimal ordering and replacement policy of a Markovian degradation system under complete and incomplete observation, respectively. However, the difference between this paper and the works stated above is the need to install a user-friendly technique to decision-making process for asset managers in order to improve the spare parts management considering the unique characteristics of CMS. In accordance with current industrial requirements, a graphical tool of this type could be easy to implement. Spare parts estimation based on reliability and environment-operational conditions is a method to improve supportability. This method can guarantee non-delay in spare parts logistics and to improve production output (Ghodrati et al., 2010).

3.2 Spare Management Performance: Condition-Based Service Level

There are several definitions to measure spare management performance. According to (Feeney & Sherbrooke, 1965) three obvious indicators are ready rate, fill rate, and units in service. Ready rate is the probability that an item observed at a random point in time has no back orders (back order is considered as any demand that cannot be met from stock). Fill rate is defined as the expected number of units demanded per time period for an item that can be immediately satisfied from stock at hand. Meanwhile, units in service are the expected number of units in routine resupply or repair at a random point in time. The work stated by (Louit, 2007) uses the instantaneous reliability of stock term as one of its criteria for determining an optimal stock level. Instantaneous reliability is defined as the probability of a spare being available at any given moment in time. This measurement can be equivalent to fill rate. In spite of these valuable definitions, the spare part reliability concept used in this paper is significantly different. The source of this distinction is given by the critical nature of spare parts which are considered in this paper, specially its uniqueness characteristic. Usually, these kinds of critical spare parts are not available in store, thus a common concept such as fill rate is not completely applicable.

For the latter reason, it seems appropriate to introduce a new concept which we have called as "Condition-Based Service Level" (CBSL). CBSL is based on the stress-strength interference theory (Ebeling, 2005). This theory considers two main variables: a stress which is any load applied on a system and that may produce a failure (in this case, depletion on service level), and a strength which is the maximum value that system can withstand without failing. Therefore, CBSL is defined as the probability that the stress does not overcome the strength. Stress-strength interference models are widely applied in component reliability analysis (Xie & Wang, 2008). Due to the model ability to be used when probability distributions are known and, also, both stress and strength could be general in meaning (Xie & Wang, 2008), it is possible to adapt a version. For purposes of this paper, stress can be represented by lead time and strength by conditional reliability.

The paper presents a graphic method which uses CBSL as key indicator, to achieve an effective policy to define the suitable time for CMS ordering, through a rule decision based on both condition-based reliability function and a stochastic/fixed lead time. The aim of the paper is orienting the decision about CMS ordering or to continue the operation process without ordering. The reliability threshold can be chosen by each company according to their own needs of service level.

Having introduced the importance of CMS ordering process in the context of operational continuity, the rest of the chapter is organized as follows: Section 3.3 indicates the model formulation. Section 3.4 shows the associated case study. Finally, Section 3.5 reveals the conclusion of the work.

3.3 Model Formulation

In order to precise the CMS ordering decision-making, it is necessary to estimate the conditional reliability and add the influence of lead times. The following items define the calculation methodology of these aspects.

3.3.1 Conditional reliability model

For the sake of self-containment, we describe in detail relevant elements which are developed in Banjevic, Jardine, Makis, and Ennis (2001); Banjevic and Jardine (2006). Reliability function is based primarily on the Markov Failure Time Process model. The reliability function of an item can be defined as the probability of survival after a certain interval of time t. For the conditional case (namely, assuming that item has been operated by a time x), the probability of interest is $P(T > t|T > x)$, where T is the equipment lifetime. This reliability is interesting in CBM, given that it is assumed that the item has been operated until the inspection moment (Louit, 2007). It is assumed that hazard rate can be incorporated into the model using PHM, *e.g.* Cox (1972); Pascual, Martínez, Louit, and Jardine (2009); Vlok, Coetzee, Banjevic, Jardine, and Makis (2002). This method is widely accepted in order to incorporate condition data of equipment (Louit, 2007) (as used in CBM). Hence

$$\lambda(t) = \lambda(t, Z(t)) = \lambda_0(t)\mathrm{e}^{\sum_i \gamma_i Z_i(t)}, \tag{3.1}$$

where $\lambda_0(t)$ is a baseline hazard rate, while γ_i is the weight of each time-dependent covariate $Z_i(t)$. For the present paper, a Weibull-PHM was used, thus the hazard rate is

$$\lambda(t) = \lambda(t, Z(t)) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \mathrm{e}^{\sum_i \gamma_i Z_i(t)}, \quad t \geq 0. \tag{3.2}$$

The use of Non-Homogeneous Markov Process (NHMP) is of particular interest in applications of CBM (Louit, 2007; Banjevic & Jardine, 2006). Transition probabilities (from a state i to a state j, of covariates under study) can be defined as

$$L_{ij}(x,t) = P(T > t, Z(t) = j | T > x, Z(x) = i), \quad x \leq t, \tag{3.3}$$

where T is a random variable representing the failure time of the item. Note that covariates $Z(x)$ can be discretized within intervals using values ranges for a finite number of states: $0, 1, 2, \ldots, s$. For example, if the condition under study is the oil level of a motor, the states could be described through intervals with levels limits as: "low", "normal", and "dangerous".

Thus, it is possible to find a relationship between hazard rate and transition probabilities $L_{ij}(x,t)$ (Banjevic & Jardine, 2006). The reliability of interest can be obtained combining both concepts (conditional probability and PHM). The reliability at time t, given that the spare has survived until a time x, and at that time x the condition is $Z(x) = i$, is given by

$$R(t|x,i) = P(T > t | T > x, Z(x) = i) = \sum_j L_{ij}(x,t), \quad x \leq t. \tag{3.4}$$

If the matrix $\mathbf{L}(x,t) = [L_{ij}(x,t)]$ is defined and it is assumed that $\mathbf{L}(x,x) = \mathbf{I}$ (where $\mathbf{I}$ is the identity matrix), the Markov property can be used (Banjevic & Jardine, 2006). Using the methodology stated in Banjevic et al. (2001), it is demonstrable that all functions $L_{ij}(x,t), x \leq t$ satisfy the following system of equations

$$\frac{\partial}{\partial t}\mathbf{L}(x,t) = \mathbf{L}(x,t)\mathbf{L}(t) = \mathbf{L}(x,t)(\mathbf{\Lambda}(t) - \mathbf{D}(t)). \tag{3.5}$$

Let:

- $\mathbf{\Lambda}(t) = [\lambda_{ij}(x)]$ is the matrix of transition rates. The transition rates $\lambda_{ij}(x)$ can be estimated using the approach of Banjevic et al. (2001).

- $\mathbf{D}(t) = [\lambda(t,i)\delta_{ij}]$ is a diagonal matrix, with $\delta_{ij} = p_{ij}(x,x)$ (i.e., it takes the value 1 when $i = j$, and the value 0 when $i \neq j$). For this particular case, $\mathbf{D}(t) = \left[\left(\frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1} \mathrm{e}^{\sum_i \gamma_i Z_i(t)} \right) \delta_{ij} \right]$.

In order to solve the system described in Equation (3.5), two cases are identified (Banjevic & Jardine, 2006):

- Case I: If the failure rate is only a function of the condition process, namely: $\lambda(t) = g(Z(t))$. Then, the solution is given by

$$\mathbf{L}(0,t) = \mathrm{e}^{(\mathbf{\Lambda}-\mathbf{D})t}. \tag{3.6}$$

- Case II: If the failure rate is a function of age and current condition state, namely: $\lambda(t) = g(t, Z(t))$. Thus, the solution can be approximated by the following method called "product-property"

$$\mathbf{L}(k\Delta, m\Delta) \approx \prod_{i=k}^{m-1} \tilde{\mathbf{L}}[i], \tag{3.7}$$

where

$$\tilde{\mathbf{L}}[k] = \mathrm{e}^{-\int_{k\Delta}^{(k+1)\Delta} \mathbf{D}(t)dt} \mathrm{e}^{\mathbf{\Lambda}\Delta}. \tag{3.8}$$

Δ defines the approximation interval length, such that: $k\Delta \leq x \leq (k+1)\Delta$ and $(m-1)\Delta \leq t \leq m\Delta$, $k < m$ (Louit, 2007). In general, while the value of Δ is smaller, the precision of the reliability estimation is better (Banjevic & Jardine, 2006) (but also the amount of iterations will be larger).

The stated Case II corresponds to Weibull-PHM model used in this paper, because of it depends on age and condition. Then, the “product-property” method was used in order to estimate the matrix of transition probabilities, and consequently, the reliability function. In Banjevic and Jardine (2006) also is defined other method to estimate the solution of the system of equations (3.5), called “product-integral” method. However, the “product-property” method is more accurate than the “product-integral” method when larger values of Δ are used. Besides, the “product-property” method is convenient because it requires the estimation of only one transition matrix.

3.3.2 Condition-Based Service Level (CBSL)

CBSL could be estimated adapting the structure given by stress-strength interference theory (Ebeling, 2005). Let x be the stress random variable and $f(x)$ be its probability density function. Likewise, let y be the strength random variable and $f(y)$ be its probability density function. Therefore, the probability that stress does not exceed an x_0 value is

$$P(x \leq x_0) = F_x(x_0) = \int_0^{x_0} f_x(x)dx. \tag{3.9}$$

Also, the probability that strength does not exceed an y_0 value is

$$P(y \leq y_0) = F_y(y_0) = \int_0^{y_0} f_y(y)dy. \tag{3.10}$$

In order to calculate CBSL, this paper uses lead time as equivalent to stress and conditional reliability as equivalent to strength. While conditional reliability is estimated using the model described in Section 3.3.1, the work adds the effect of lead time considering two cases described by Ebeling (2005): (i) stochastic lead time (stress) and stochastic conditional reliability (strength), and (ii) constant lead time (stress) and stochastic conditional reliability (strength).

3.3.2.1 Stochastic lead time and stochastic conditional reliability

If both variables are stochastic, CBSL is the probability that lead time (stress) is less than conditional reliability (strength). Or equivalently, the probability that conditional reliability exceeds lead time. As a result, CBSL is given by

$$\begin{aligned} \text{CBSL} = P(x \leq y) &= \int_0^\infty \left[\int_0^y f_x(x)dx \right] f_y(y)dy \\ &= \int_0^\infty F_x(y) f_y(y)dy. \end{aligned} \tag{3.11}$$

Figure 3-1 exhibits the CBSL which is defined by the area where both tail curves overlap or interfere with each other. This interference analysis between stress and strength is the reason of the theory name.

3.3.2.2 Constant Lead time and Stochastic Conditional Reliability

If the lead time is a known constant value x_s and conditional reliability is a random variable, then CBSL is the probability that conditional reliability exceeds the constant lead time. Hence

$$\text{CBSL} = P(y \geq x_s) = \int_{x_s}^\infty f_y(y)dy. \tag{3.12}$$

Consequently, this instance could be considered as a special case of when both stress and strength are stochastic.

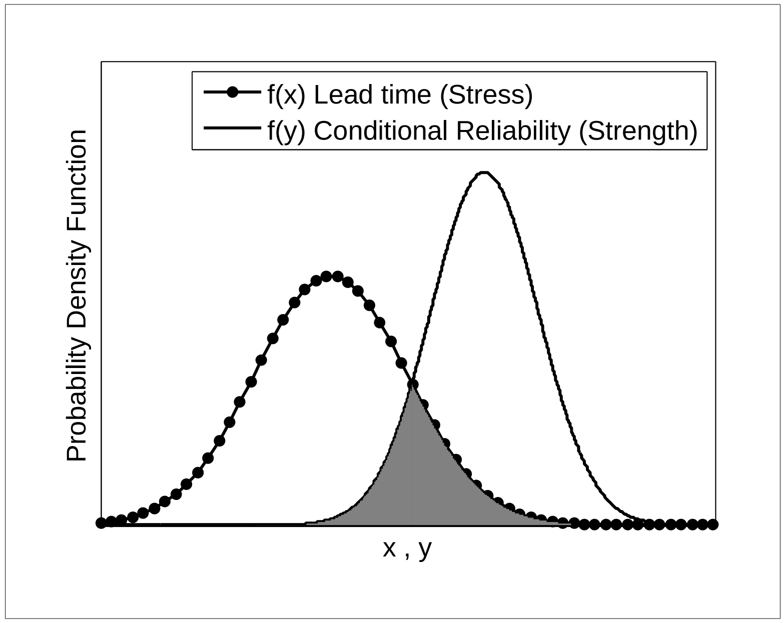

Figure 3-1: CBSL as overlap of conditional reliability and lead time

3.3.3 Spare part ordering decision rule

Considering a deterministic lead time L, spare part ordering time T_o is defined by time T_{th} at which desired reliability threshold R_{th} is reached. Note that often a constant lead time is not the case and variations on the delivery time exist (Pascual, Martínez, et al., 2009). Companies can choose several scenarios of reliability threshold in order to obtain a given service level. Therefore, the decision rule can be described by

$$T_o = \inf\{t \geq 0 : L \geq T_{th}\}. \tag{3.13}$$

Figure 3-2 illustrates this rule. It uses data from a numerical example given by Banjevic and Jardine (2006). If lead time L is less than T_{th} at a given inspection time t (case shown by L_1) then equipment can continue operating with the same spare part, because there is enough time until the arrival of a new spare faced with a potential need (because of the policy to keep reliability R_{th}).

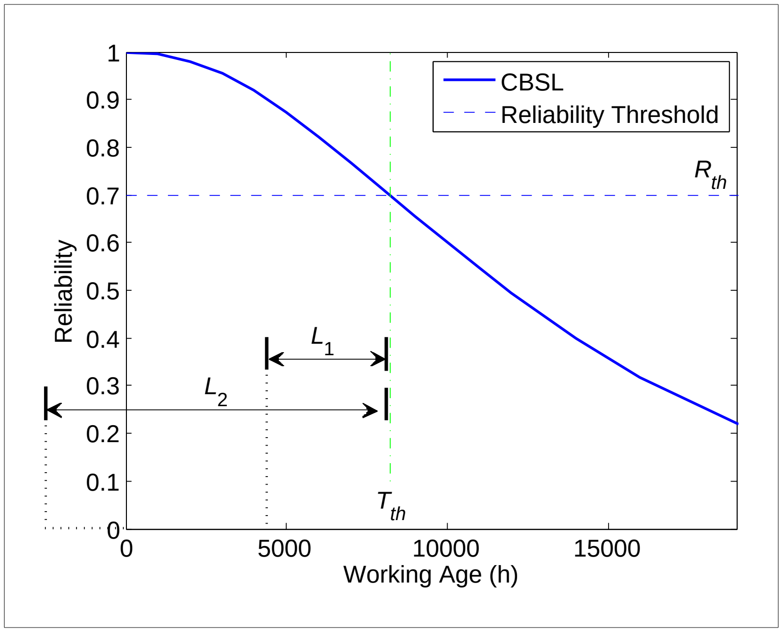

Figure 3-2: Spare part ordering decision rule

If lead time L is greater than T_{th} (case shown by L_2) then an ordering decision is required, otherwise spare part will not be able to ensure the operational continuity of the equipment supported by the spare-stocking. If lead time L and T_{th} are equal then an ordering decision must be also made, because this situation is likely to require a setup time for the new spare part.

3.4 Case Study

The following case is an adapted version of a case study described by Pascual, Martínez, et al. (2009). The spare of interest is an electric motor of a mining haul truck and, based on expert judgement, oil is the key factor to model the condition process. Table 3-1 describes the model parameters. Covariates were discretized in three bands, as shown in Table 3-2. In addition to, Table 3-3 indicates the estimated matrix of transition probabilities.

Table 3-1: Baseline hazard rate parameters for electric motor

Parameter	Value	Units
β	3.5	
η	19003	(h)
γ	0.0001742	(ml/particles)

Table 3-2: Oil initial system states and covariate bands

Initial state	Covariate band (ml/particles)	State value (particles/ml)
State 0	$(0 \ldots 53.73)$	7
State 1	$(53.73 \ldots 87.91)$	76.5
State 2	$(87.91 \ldots \infty)$	11586

Table 3-3: Transition probabilities for motor condition

j	1	2	3
p1-j	0.99797	0.00202	0.00001
p2-j	0.00159	0.99832	0.00009
p3-j	0.00317	0.00181	0.99505

Figure 3-3 shows the conditional reliability function estimated for 3 different initial states of oil, using the methodology indicated in Section 3.3.1. Working ages have been set in operational hours (h).

Furthermore, conditional reliability is fitted with a Weibull distribution for different initial survival times ($t_0 = 0$ (months), $t_0 = 12$ (months), and $t_0 = 24$ months)).

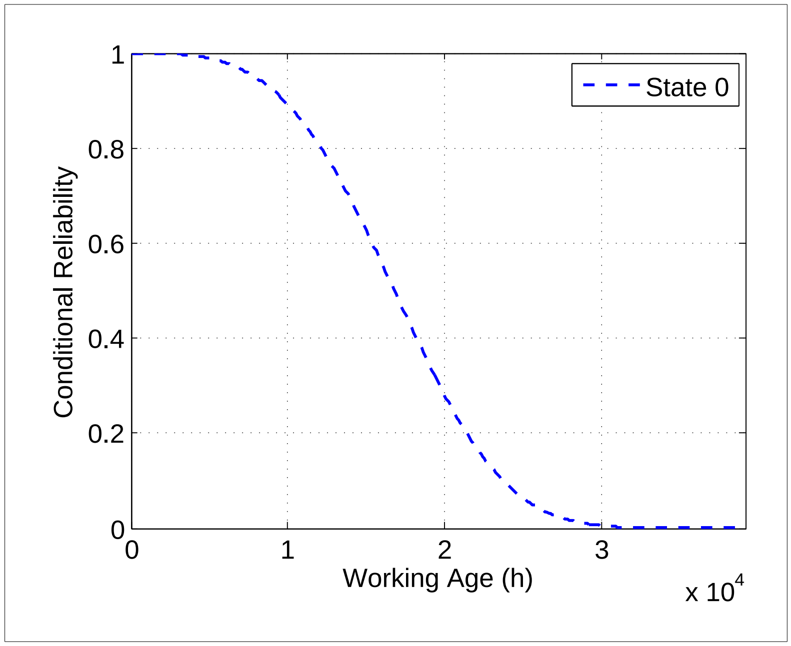

Figure 3-3: Conditional reliability function at different oil initial states

Figure 3-4 displays the model fit. A Kolgomorov-Smirnov test was applied to prove the model and the results were satisfactory.

Having set the Weibull distribution for conditional reliability and considering the CBSL definition, the two cases mentioned in Section 3.3.2 are tested. Firstly, the case where both lead time (stress) and conditional reliability (strength) are stochastic. Secondly, the case where conditional reliability is stochastic, but lead time is constant.

3.4.1 Condition-Based Service Level considering stochastic lead time

We tested using different distributions for lead time (including constant lead time in next section). In this sense, the aim is determining the capability to withstand the lead time variability. The choice of any lead time distribution is defined by delivery constraints of spare part supplier. Figure 3-5 exhibits

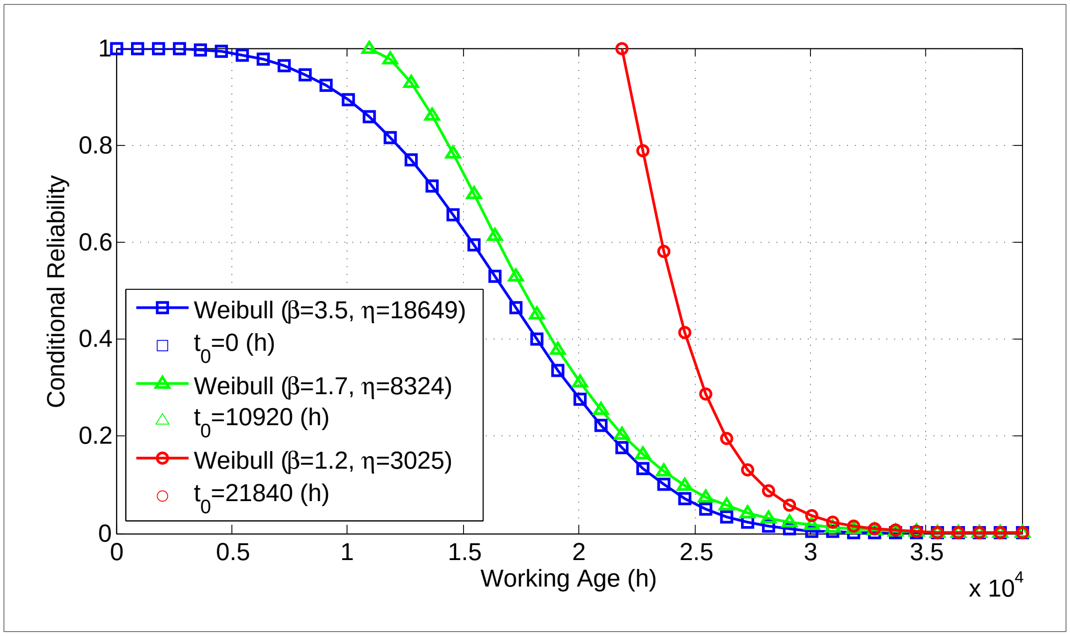

Figure 3-4: Weibull model fit for conditional reliability for different initial survival times

four distributions which are considered to fit lead time, namely: Exponential, Truncated Normal, Weibull with 2 parameters (Weibull (2p)), and Weibull with 3 parameters (Weibull (3p)). The same mean is set for all distributions. Using an estimated operational utilization of 80%, mean lead time is set at 2,730 (h) (3 operational months).

Figure 3-6 exhibits a performance realization as a result of evolution over time (t) because of interaction between conditional reliability and lead time. Conditional reliability has been fitted as a Weibull (2p) distribution. Figure 3-7 is a top view of the same realization which illustrates that CBSL (probability that strength is greater than stress) is declining as the conditional reliability decreases. In other words, component is becoming older over time because the evolution of condition, thus service level is also declining.

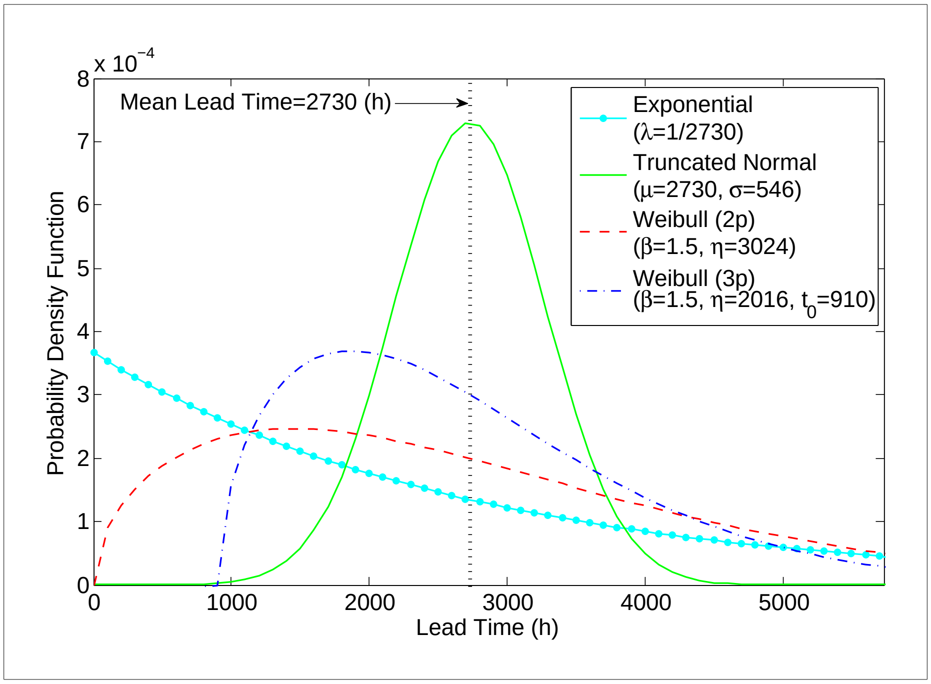

Figure 3-5: Probability density functions versus lead time

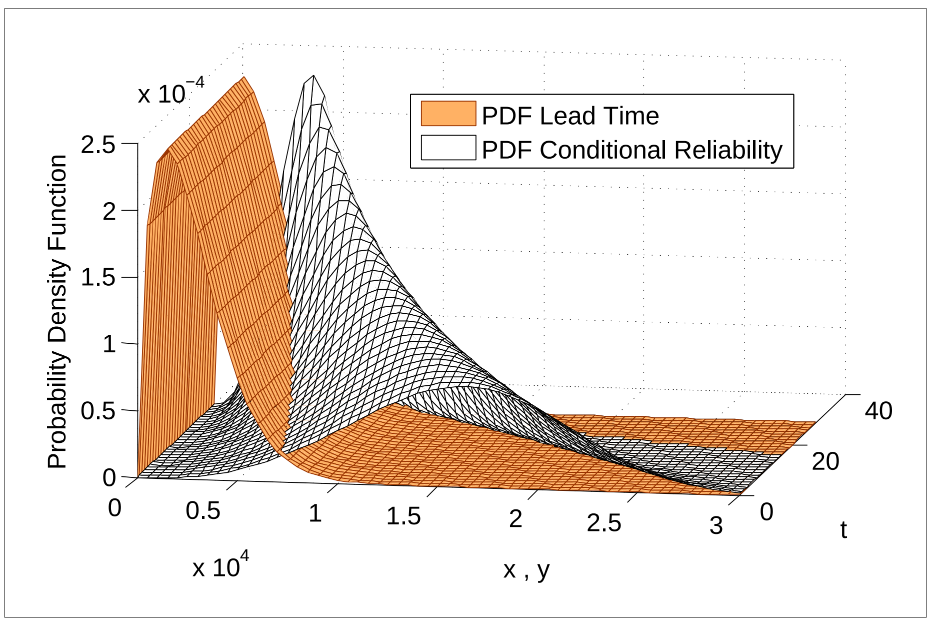

Figure 3-6: Performance realization of stress versus strength

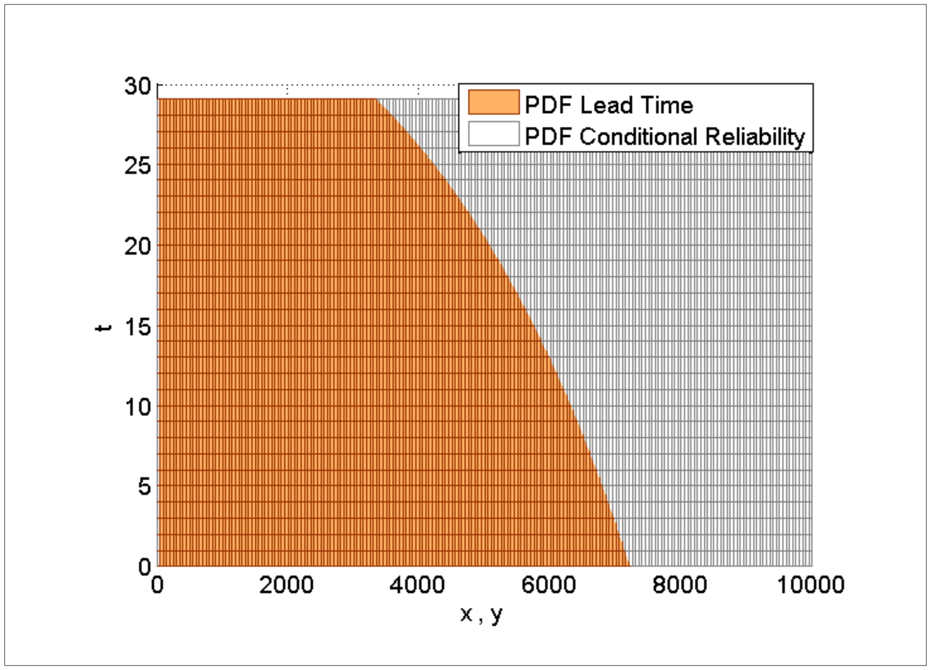

Figure 3-7: Top view of CBSL for a given realization

Figures 3-8, 3-9, 3-10, and 3-11 show the values of CBSL for different scenarios of mean lead time and for different initial survival times. Standard deviation depends on each distribution. If CBSL is greater than a given reliability threshold R_{th}, then the system is able to resist stress satisfying the desired service level. Thus, equipment can continue operating and a spare part order is not necessary. On the other hand, if CBSL is less than R_{th}, then a spare part order is mandatory because of spare part will not be able to withstand the lead time variability, and the desired reliability would not be accomplished.

3.4.2 Condition-Based Service Level considering constant lead time

Table 3-4 evidences the decision-making for different reliability thresholds and their respective working ages, where spare part ordering depends on the decision rule (Section 3.3.3). In the current case, three threshold values are considered, namely: 99%, 95%, and 90%. Three lead time scenarios in order

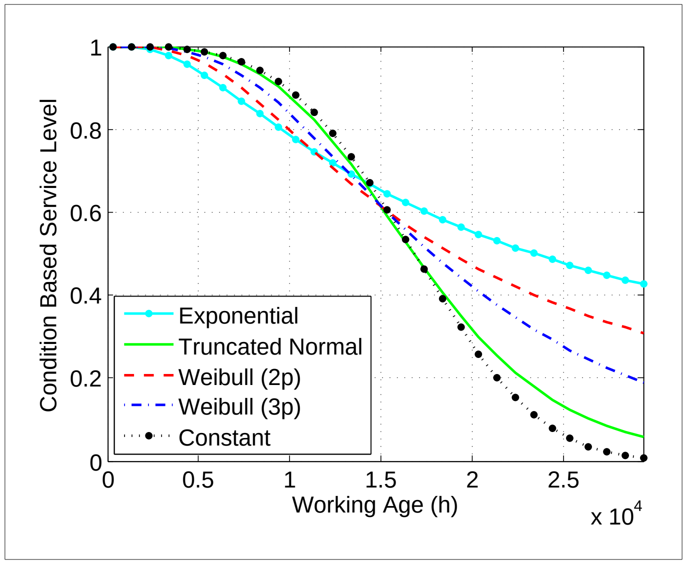

Figure 3-8: CBSL for initial survival time of 0 (months)

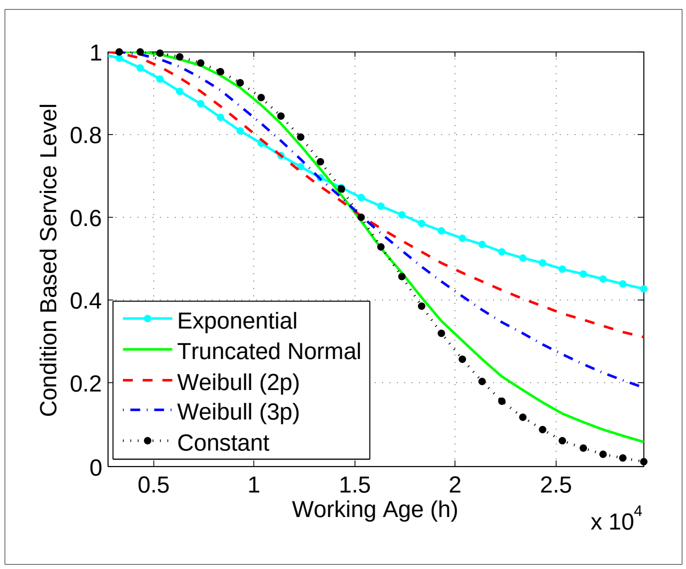

Figure 3-9: CBSL for initial survival time of 3 (months)

to realize the effect of them on service level are considered. Markov reliability model allows setting any initial condition for spares. In this regard, a complete range of practical operational environments can be represented. For instance,

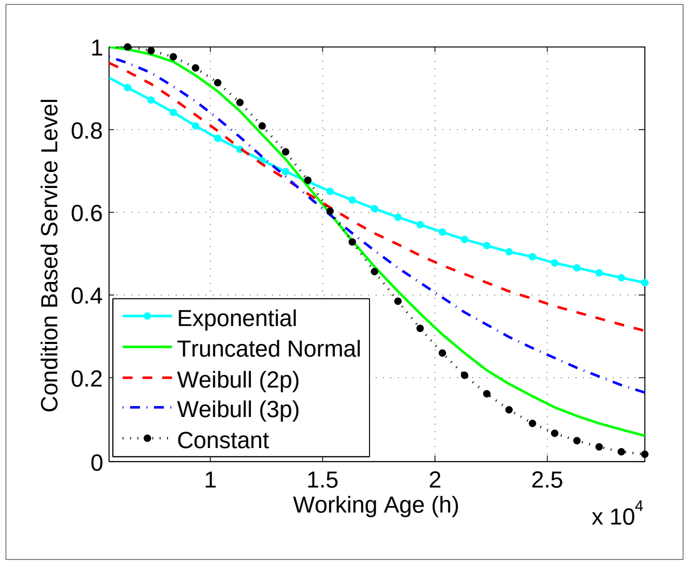

Figure 3-10: CBSL for initial survival time of 6 (months)

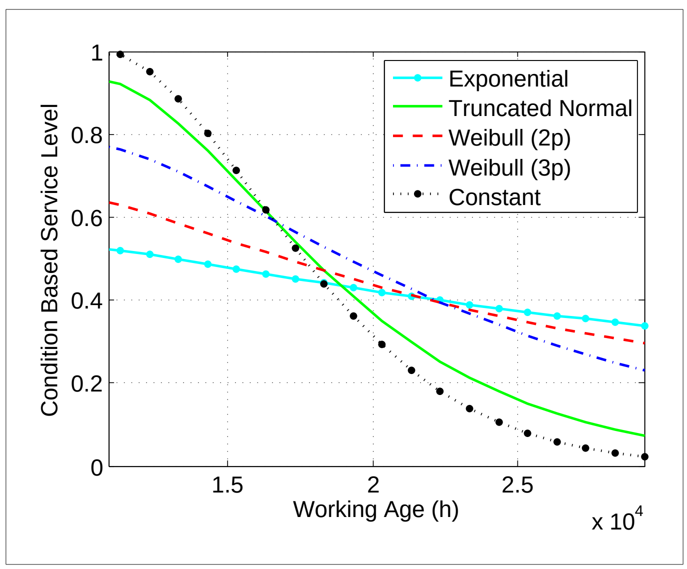

Figure 3-11: CBSL for initial survival time of 12 (months)

if it is assumed that the motor is new, then the initial condition is “as-good-as new” (“State 0”).

Table 3-4: Motor ordering decision for different reliability thresholds and lead time scenarios

Expected lead time : 910 (h) (1 month)						
	Expected time (h)			Ordering decision		
Reliability threshold	State 0	State 1	State 2	State 0	State 1	State 2
99%	494	467	122	**Order**	**Order**	**Order**
95%	1753	1723	1067	Continue	Continue	Continue
90%	3100	3074	2518	Continue	Continue	Continue

Expected lead time : 2,730 (h) (3 months)						
	Expected time to order (h)			Ordering decision		
Reliability threshold	State 0	State 1	State 2	State 0	State 1	State 2
99%	494	467	122	**Order**	**Order**	**Order**
95%	1753	1723	1067	**Order**	**Order**	**Order**
90%	3100	3074	2818	Continue	Continue	Continue

Expected lead time : 5,460 (h) (6 months)						
	Expected time to order (h)			Ordering decision		
Reliability threshold	State 0	State 1	State 2	State 0	State 1	State 2
99%	494	467	122	**Order**	**Order**	**Order**
95%	1753	1723	1067	**Order**	**Order**	**Order**
90%	3100	3074	2518	**Order**	**Order**	**Order**

As expected, when lead time is increasing, reliability constraints are more demanding and ordering decision time turns sooner. As shown in Table 3-4, for a reliability threshold of 95%, the decision changes from "continue" without ordering to "order" the spare, when the lead time increases from 847 (h) to 3388 (h). On the other hand, initial condition states also play a role. For a lead time of 1694 (h) and at the same reliability threshold of 95%, a greater deterioration level makes to change the decision from "continue" to"order".

Working age of this decision map makes practical sense until approximately 6 months of expected lead time. If lead time is greater than that period, then

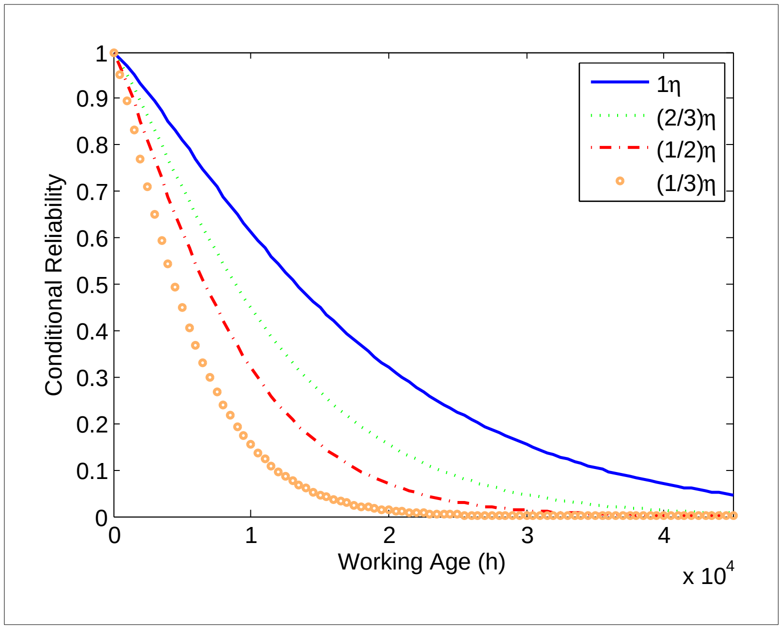

Figure 3-12: Conditional reliability considering aging by depletion of η

it could be better to stock spare parts. However, CMS are unique and are not backed-up. Therefore, another important factor is when the component becomes older. Figure 3-12 demonstrates this situation, considering different scenarios of η to a situation of increasing aging. Table 3-5 displays the same decision map but considering $(2/3)\eta$ from the original value.

Using new η, the situation becomes critical at a lower time. With the original model, the scenario of "always ordering" happened just at 6 months. With new η, the decision of "always ordering" should be already made with any initial state at 3 months. This is relevant because if lead time is 6 months, spare parts should be purchased as soon as the component starts to operate. Then, with this map is also possible to visualize those parts that can be classified as insurance spares.

Table 3-5: Motor ordering decision for different reliability thresholds and several lead time scenarios by depletion of η

Expected lead time : 910 (h) (1 month)						
	Expected time (h)			Ordering decision		
Reliability threshold	State 0	State 1	State 2	State 0	State 1	State 2
99%	284	283	227	**Order**	**Order**	**Order**
95%	1074	1068	917	Continue	Continue	Continue
90%	1905	1897	1691	Continue	Continue	Continue

Expected lead time : 2,730 (h) (3 months)						
	Expected time to order (h)			Ordering decision		
Reliability threshold	State 0	State 1	State 2	State 0	State 1	State 2
99%	284	283	227	**Order**	**Order**	**Order**
95%	1074	1068	917	**Order**	**Order**	**Order**
90%	1905	1897	1691	**Order**	**Order**	**Order**

Expected lead time : 5,460 (h) (6 months)						
	Expected time to order (h)			Ordering decision		
Reliability threshold	State 0	State 1	State 2	State 0	State 1	State 2
99%	284	283	227	**Order**	**Order**	**Order**
95%	1074	1068	917	**Order**	**Order**	**Order**
90%	1905	1897	1691	**Order**	**Order**	**Order**

3.5 Conclusions

This work provides a technique to enhance spare parts ordering decision-making when companies need to ensure a reliability threshold restricted by a lead time. Case study showed that condition data could be an accurate indicator of component state affecting the shape of reliability function. The ordering process can be affected by different initial survival times and initial condition states; they can change the decision for same reliability threshold even. On the other hand, lead time is a relevant factor in ordering decision. The ordering policy is sensitive to different scenarios of lead times; they can also modify the spare part ordering decision if the aim is ensuring the operational continuity of the equipment supported by the spare part stock. It was concluded that, in order to fulfill with operational continuity, condition data can be a powerful tool for including in spare management. The need of focus on critical spares and severe consequences on equipment performance, demands a friendly technique which can be used in an environment where decisions are needed quickly, in this regard, the presented decision rule is easy to implement graphically and it can be used by asset managers to enhance operational continuity.

3.6 Acknowledgements

The authors wish to acknowledge the partial financial support of this study by the FOndo Nacional de DEsarrollo Científico Y Tecnológico (FONDECYT) of the Chilean Government (project 1130234).

4. VALUE-BASED OPTIMIZATION OF REPLACEMENT INTERVALS FOR CRITICAL MINING COMPONENTS

I can make a General in five minutes but a good horse is hard to replace.
— ABRAHAM LINCOLN

Critical equipment are the functional basis of performance on operating lines of asset-intensive industries. In the support of this kind of equipment, spare parts play a fundamental role. Critical spares are associated with both significant investment and high reliability requirements. Their mismanagement leads to considerable impacts on financial structure and severe consequences on operational continuity. Concordantly to this economical criticality, there usually are few, or just zero, critical spares available at stores. In order to overcome the need for spare-stocking, it appears the necessity for techniques with the capacity to predict failures of spare parts before catastrophic situations occur. An efficient method to deal with this situation is monitoring spares conditions through Condition-Based Maintenance (CBM). Nevertheless, optimal CBM decisions are based on minimization of direct maintenance costs, which can misguide the orientation of business objectives.

Value-adding demands enriched methods for enhancing efficiency, reliability and profitability of decision-making processes. Continuous improvement of performance is required by the increasing competitiveness in which companies are currently involved. Desired and sustainable outcomes can be accomplished through an optimal approach of managing assets (International Organization for Standarization, 2012). Asset management has evolved from having a narrow purpose of just fixing broken items, to a strategic wider role covering the whole life cycle system and securing future maintenance requirements (Jardine & Tsang, 2006). This perspective creates a need for excellent practices. Asset management excellence pursues exceptional plant efficiency by means of balancing performance, risk, and cost within a random-nature industrial environment (Campbell et al., 2011). Accordingly, competitive industries cope with an unceasing exigency to add value in their processes.

Growing business performance targets can be addressed by using reliability models. From the maintenance excellence viewpoint, the optimization of asset replacement and resource requirements decisions is essential for the continuous improvement (Jardine & Tsang, 2006). This becomes even more decisive in the case of asset intensive industries –such as Mining, Aeronautic, Defense, or Nuclear industries– with high investment equipment to perform operations. The constant pressure to reduce costs and increase utilization often leads to a stress on equipment, affecting reliability and throughput (Godoy et al., 2013). Hence, the interest lies in improving the system reliability. The operation of essential equipment is supported by critical components (Louit, 2007). Consequently, reliability enhancement of complex equipment can be achieved by preventive replacement of its critical components (Jardine & Tsang, 2006). Critical major components are often expensive and need high reliability standards, they are habitually related to extended lead times and influence on production and safety (Godoy et al., 2013). They are often related to lengthy plant shutdowns with associated production losses. These expected losses have a significant impact on tactical, financial, and logistic considerations. As a mitigation measure to this impact, critical components are monitored by using Condition-based Maintenance (CBM) (Godoy et al., 2013). Examples of these items within the Mining industry are: mill liners, shovel swing transmissions, and haul truck engines. The challenge is to identify an optimal change-out epoch to intervene in major critical components in order to meet both reliability constraints and business goals.

Business-market conditions have the potential to change major components optimisation decisions. Replacement optimisation criteria depend on objectives that firms attempt to achieve. Internal scheduling principles, such as cost or availability, are traditionally preferred for setting maintenance intervention policies. Cost minimization is based on the assumption to balance both replacement and operating costs (Jardine & Tsang, 2006).

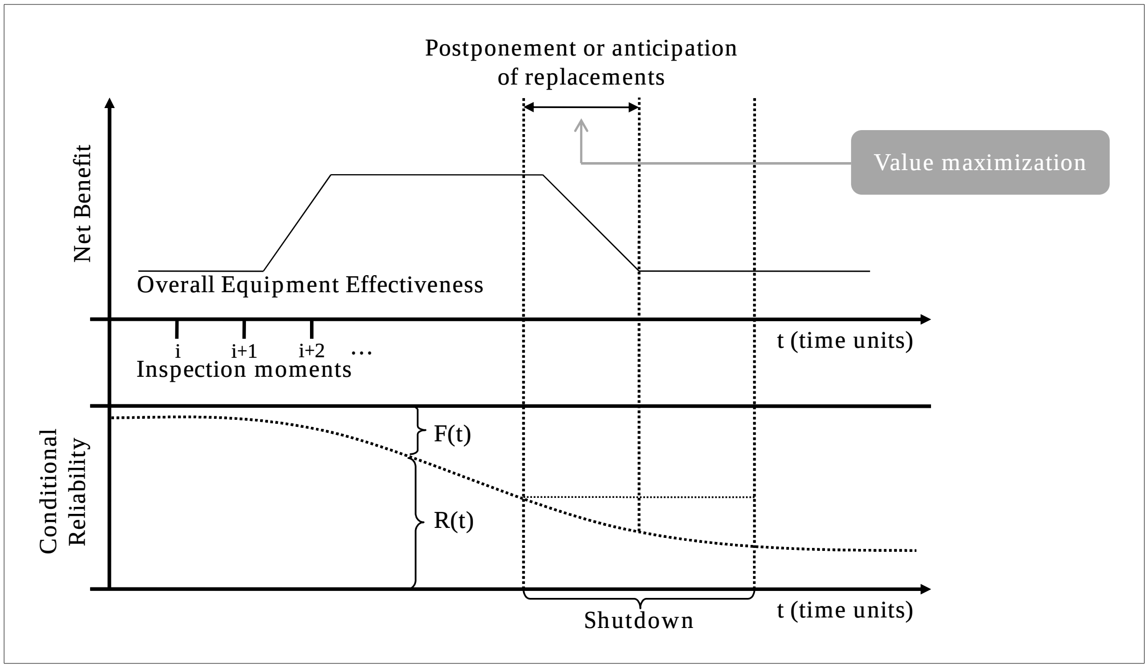

Figure 4-1: Value-adding decision rule

In turn, availability maximization (or downtime minimization) is in search of a balance between preventive replacement downtime and failure replacement downtime (Campbell et al., 2011). Using this kind of criteria, an optimal components overhaul and replacement policy can be properly defined to accomplish internal performance targets. Nevertheless, these widely-used practices do not usually consider relevant external factors, such as current business scenario at replacement epoch. Commodities price is an example of these external conditions in asset intensive industries. Different commodity prices (e.g. copper) may postpone or accelerate cost-based replacement decisions. If a favourable-price scenario is faced, then it could be more profitable to delay the intervention epoch and continue operating. This decision, however, needs to be balanced against the risk of unplanned failure. Figure 4-1 describes this decision rule. Although the minimum cost would still be an optimal point, external conditions should modify replacement policies in pursuit of increasing revenues and adding value. In consequence, internal criteria might disregard valuable decision-making information, which can be covered when business conditions are taken into account.

In order to overcome the abstraction from business conditions, we have proposed a component replacement policy focused on economic benefits over the time-span given by major shutdowns. To estimate revenues, several commodity price scenarios have been contemplated during intervention time-windows. Instead of exclusive consideration of involved costs, the criterion is based on both maximization of revenue and achievement of reliability goals. For purposes of this work, this approach has been termed value-adding. In order to meet business needs, the question arises from addressing the best moment to intervene. The purpose is to take advantage of extra-benefits at favorable commodity prices epochs. Therefore, the aim of this work is to advise the decision-making process about the best epoch to replace major components under the value-adding criterion. The paper presents a model to establish such optimal epoch. Variables examined are estimation of net benefits subject to an interest rate for discounting, commodity prices, condition-based reliability, intervention costs, and expected downtime during major component shutdowns.

Relevant assumptions and limitations of the model are the following:

- It is not intended to provide a perfect forecast of copper prices, but rather the objective as value-adding is to include other relevant decision factors in addition to traditional cost minimization.
- Following previous idea, value creation can be considered as the difference between free cash flow and capital employed multiplied by the weighted average cost of capital (Adams, 2002).
- Short-term models are not suitable for the kind of components of this work. Major intervention intervals are set by several months or even years, and associated shutdowns by weeks.

Once the relevance of both reliability and production value conditions in CBM decisions has been introduced, the rest of this chapter is structured as follows. Section 4.1 describes the model formulation which includes the value-adding as major component intervention criterion. Section 4.2 illustrates a case study for the Mining industry. In Section 4.3, conclusions about the application are announced.

4.1 Model formulation

As discussed, this model attempts to establish an optimal change-out epoch to intervene in major critical components under an entire maintenance process value criterion. The following sections describe the calculation methodology of conditional reliability function and value-adding optimization model.

4.1.1 Conditional reliability function

The reliability function of an item is its probability of survival over a certain time interval. Let $P(T > t|T > x)$ be the conditional probability, where T is the lifetime of the component which has already been operated by a time x. As a CBM strategy has been selected, it is necessary to estimate a hazard rate $\lambda(t)$ which includes the equipment condition. Proportional Hazards Model (PHM) (Cox, 1972) allows incorporating this conditional information. In this work, a hazard rate from Weibull-PHM model is used. Where γ_i is the weight of each time-dependent covariate $Z_i(t)$ which describes the condition process of interest.

$$\lambda(t) = \lambda(t, Z(t)) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \mathrm{e}^{\sum_i \gamma_i Z_i(t)}, \quad t \geq 0. \tag{4.1}$$

A conditional reliability function has been set following the procedure described in Banjevic and Jardine (2006). Let $L_{ij}(x, t)$ be the transition probabilities of covariates under study (from a state i to a state j) defined by the following Non-Homogeneous Markov Process

$$L_{ij}(x,t) = P(T > t, Z(t) = j | T > x, Z(x) = i), \quad x \leq t. \tag{4.2}$$

Therefore, the reliability at time t, given that the critical component has survived until a time x with a condition $Z(x) = i$, is estimated by

$$R(t|x,i) = P(T > t | T > x, Z(x) = i) = \sum_j L_{ij}(x,t), \quad x \leq t. \tag{4.3}$$

4.1.2 Traditional cost optimization models

In case of short-term component replacement decisions, (Jardine & Tsang, 2006) suggest the minimization of total expected cost per unit time $C(t_p)$, as the ratio between the total expected replacement cost per cycle and the expected cycle length. Where C_p and C_f are the total cost of a preventive replacement and a failure replacement, respectively, and $M(t_p)$ is the mean time to failure. Hence, the model in order to find an optimal age t_p to perform a component replacement is

$$C(t_p) = \frac{C_p R(t_p) + C_f F(t_p)}{t_p R(t_p) + M(t_p) F(t_p)}. \tag{4.4}$$

In case of long-term capital equipment replacement decisions, the need for including an interest rate for discounting is addressed. The goal is to establish an optimal replacement age n to minimize total discounted cost $C(n)$. The model presented by Jardine and Tsang (2006) is

$$C(n) = \frac{\sum_{i=1}^{n} C_i r^i + r^n (A - S_n)}{1 - r^n}, \tag{4.5}$$

where C_i is the operation and maintenance cost in the i^{th} period, A is the acquisition cost of capital equipment, S_n is the resale value of equipment, and $r = \left(\frac{1}{1+\text{interest rate}/100}\right)^n$ is the discount factor.

4.1.3 Value-adding optimization model

Although the usefulness of previous optimization models presented, unique characteristics from major critical components considered in this work make the need for a new concept. Replacement of these components cannot be treated as a short-time decision; thus, the model from Equation (4.4) is not completely applicable. On the other hand, though these components are not exactly capital equipment, their replacements imply medium-long term decisions as the model from Equation (4.5). Hence, a combination of both models is a suitable option for major critical component replacement. As discussed by Jardine and Tsang (2006), when the time value of money is incorporated into analyses of discounted benefits (or equivalently value-adding V, as contemplated in this work)

$$\max(V) = \max\left[v(t_r) + v(t_r)r^i + v(t_r)r^{2i} + \ldots + v(t_r)r^{(n-1)i}\right]. \tag{4.6}$$

Rather than using $\left[\frac{v(t_r)}{t_r}\right]$ as in short-term models, maximizing benefits is equivalent to

$$\max(V) \equiv \max\left[\frac{v(t_r)}{1-r^n}\right]. \tag{4.7}$$

In consequence, the goal of this value-adding optimization is addressing both business goals and conditional reliability from CBM strategies. This new model has been designed as follows.

Net benefits, $\text{NB}(t_r)$, are given by

$$\begin{aligned}\text{NB}(t_r) &= \text{Revenues}(t_r) - \text{Operating Costs}(t_r) \\ &= (P_{lb}(t_r) - C_{lb}(t_r))\,\text{Production}(t_r),\end{aligned} \tag{4.8}$$

where P_{lb} and C_{lb} are the market commodity price and the production cost, respectively.

As benefits, $\text{BEN}(t_r)$, are dependent on conditional reliability function, then

$$\text{BEN}(t_r) = \text{NB}(t_r) \cdot \text{OEE} \cdot R(t|x,i), \tag{4.9}$$

where $\text{OEE} = \text{Utilization} \times \text{Performance} \times \text{Quality}$.

Intervention replacement costs (C_{rp}) per cycle are set as done by traditional models, but using CBM conditional reliability and with the distinction given by analysis from Equation (4.9), as follows

$$C_{rp} = C_p \cdot R(t|x,i) + C_f \cdot F(t|x,i). \tag{4.10}$$

When dealing with costs, models habitually only consider intervention costs. To surpass this limitation, breakdown cost (C_{bd}) during components shutdown has been added.

$$C_{bd} = c_s \int_{t_i}^{t_i + \Delta \text{shutdown length}_i} (1 - R(t|x,i))dt, \tag{4.11}$$

where the shortage cost rate c_s is the production loss caused by the equipment downtime.

The aim is to establish a major critical component replacement interval (n) that maximizes the profit net margin between discounted benefits $\text{BEN}(t_r)$ and replacement costs, over a long period, rather than only cost minimization.

Thus, the model for maximizing value is defined as

$$\max\left(V(n)\right) \equiv \max\left[\frac{\sum_{i=1}^{n} \mathrm{BEN}_i r^i - \left(\sum_{i=1}^{n}\left(C_{rp}+C_{bd}\right) r^i + r^n\left(A - S_n\right)\right)}{1-r^n}\right]. \tag{4.12}$$

Due to the kind of components dealt in this work, S_n could be ignored. Equivalent Annual Cost (EAC) can be calculated using the capital recovery factor (CRF) as follows: EAC $= \max\left(V(n)\right) \cdot$ CRF. When models are based on a geometric progression over an infinite period, then CRF equals the interest rate.

4.2 Case study

The following is an adapted version of a case study described by Pascual, Martínez, et al. (2009). The critical component of interest is a motor stator on a SAG mill in a northern Chile mining firm. Expert criterion has suggested setting oil as the factor to explain the condition process $(Z_i(t))$. After the conditional reliability is calculated, the optimal replacement times under both minimization of costs and value-adding optimization are compared.

4.2.1 Condition-based reliability

As discussed in the methodology section, estimated parameters using Weibull-PHM are: β = 3.35, η = 22,531 (h), and γ = 1.74210^{-4} (ml/particles). Table 4-1 indicates the matrix of transition probabilities.

Figure 4-2 shows the conditional reliability function using the methodology described in section 4.1.1. Despite a continuous degradation through the time-span, oil levels are assumed to be in the best level at the beginning

Table 4-1: Transition probabilities for motor stator condition

j	1	2	3
p1-j	0.99797	0.00202	0.00001
p2-j	0.00159	0.99832	0.00009
p3-j	0.00317	0.00181	0.99505

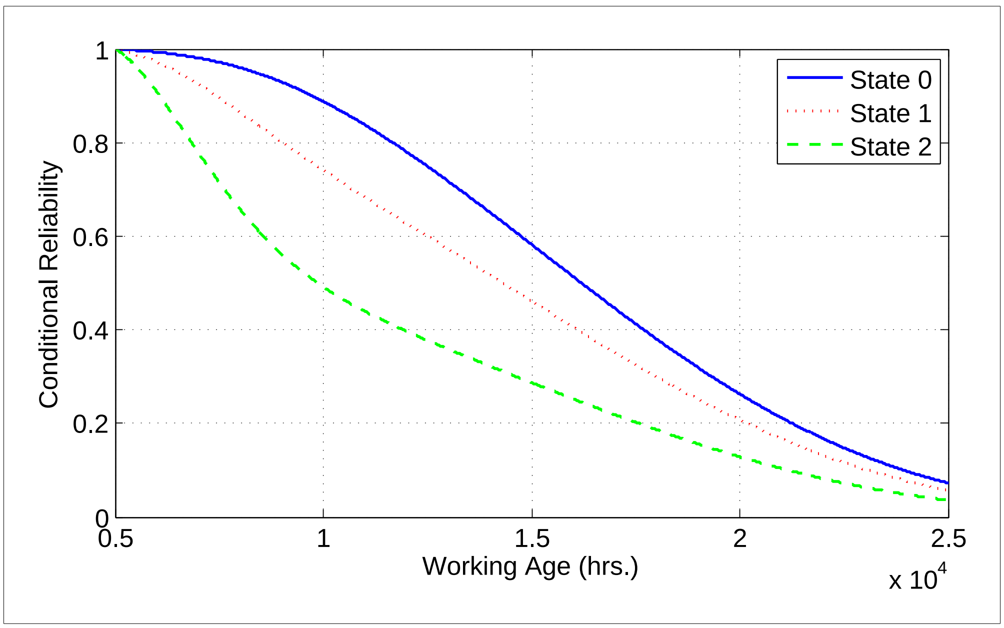

Figure 4-2: Weibull-PHM conditional reliability for different initial states of oil

of the analysis, *e.g.* at component installation moment. The application of a Kolgomorov-Smirnov test on model results has been satisfactory. This estimated reliability is used as output for optimization models presented in the following sections.

Table 4-2: Cost parameters for optimization model

Parameter	Value	Units
Preventive replacement cost	150,000	US$
Corrective replacement cost	318,000	US$
Shortage cost rate	2,349	US$/h
Acquisition cost	900,000	US$

4.2.2 Application of traditional cost optimization model

Table 4-2 lists cost parameters used in this case study. It is assumed no resale value of replaced component. Interest rate for discounting is 10% annual. After adapting Equation (4.12) for only consideration of internal costs, the optimal replacement time is estimated as: 17 (months) with a total discounted cost of US$ 1,822,247 (EAC = US$ 190,813).

4.2.3 Application of value-adding optimization model

Net benefits were calculated through an estimation of commodity prices during the study period. A lesson learned from this process is explained as follows. In the first place, a Markov process was used and validated by 3 years of copper prices historical data. But then, as the idea is to facilitate the model applicability, a simpler but reasonable moving average method was used. Mean squared errors from moving average were sufficiently close to more advanced methods, such as exponential and logistic autoregressive models (ESTAR and LSTAR) or first-order autoregressive process AR(1). See Engel and Valdés (2002) for a further explanation of these methods on copper price forecasts.

Inspection periods were set by trimesters. Hence, OEE was also varying through the case study length. Namely, utilization and productivity were

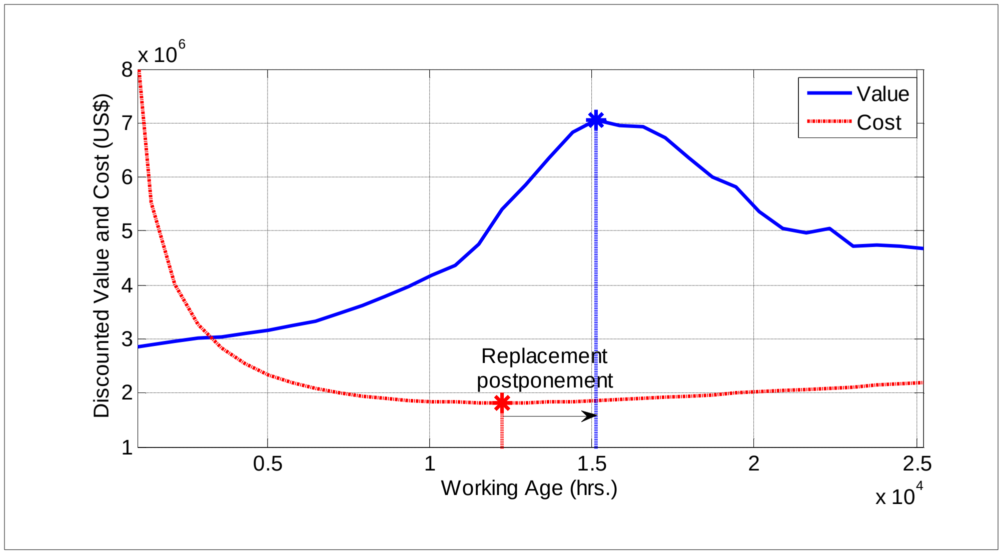

Figure 4-3: Comparison of optimal replacement times under cost and value-adding optimizations

changing during the scope time. Therefore, the best time to replace the motor stator under value-adding maximization criteria is by: 21 (months). The highest net benefit is achieved at this time. Thus, the discounted value $V(n)$ is: US$ 7,058,243 (EAC = US$ 739,090). Figure 4-3 illustrates a comparison between cost optimization model and value-adding model. Optimal points from both criteria denote the difference of replacement epochs. If value-adding criterion is adopted, then replacement decision is postponed by 2830 (hours), approximately 4 (months). This new epoch should be a helpful factor in long-term major shutdowns planning.

Despite of this is a particular case, it is clear to note that when both value creation and reliability are taken into account rather than internal costs, the critical component replacement epoch is highly susceptible to be modified (postponed or accelerated) in favor of financial strategy.

4.3 Conclusions

This work has presented a model to determine the optimal epoch to replace major critical components with lengthy shutdowns associated, under a value-adding criterion which allows addressing both conditional reliability and business goals. It has been shown that conditional reliability under a CBM strategy is a suitable input to replacement methods, as a measure of performance monitoring of high financial impact components. Value creation strategy has enriched the decision-making process, by quantifying the real value of postponing or accelerating the right epoch to perform an intervention. Copper prices were included into value-adding analyzes, but performance measurements, such as OEE, are reasonable options. Rather than an accurate prediction of commodity prices, the general aim of this work is to diffuse a new concept in pursuit of business goals instead of simply cost minimization. Due to the fact that the components considered support critical equipment, model results have the potential to be useful decision elements in long-term major shutdowns planning. Continuous improvement and firm profitability is favored when value-adding approach is included in asset management conception, as a systemic viewpoint of the whole business.

5. OPTIMIZING MAINTENANCE SERVICE CONTRACTS UNDER IMPERFECT MAINTENANCE AND A FINITE TIME HORIZON

Our success has really been based on partnerships from the very beginning.
— BILL GATES

The introduction of standards such as the impending ISO 55001 (International Organization for Standarization, 2012) or PAS-55 (British Standards Institution, 2008) , and the increasing concern on sustainable manage life cycle costs have intensified the use of asset management techniques to estimate resources from system design, to operation and disposal (Jardine & Tsang, 2006; Lugtigheid et al., 2007). One way to achieve that is to balance in-house resources and to outsource business functions like maintenance.

Before the 1970s, most equipment maintenance was done with in-house resources. Nevertheless, due to the systems have been growing in complexity, it is more competitive that system service can be supplied by specialized external agent with specialized equipment (Ding, Lisnianski, Frenkel, & Khvatskin, 2009). In the last decade, maintenance outsourcing has significantly increased its relevance. Outsourcing has become a business key to reach a competitive advantage, since products and services can be offered by outside suppliers in a more efficient and effective way (Yang, Kim, Nam, & Min, 2007). There has also been a paradigm shift in asset management, in which maintenance has evolved from a cost-generating activity to a value-adding function; nowadays, outsourcing is viewed as a mode not only to ensure cost objectives, but also accessing better quality of service and improving the product delivery capability (Kumar, 2008). Outsourcing also involves risk transfer. The cost of this transfer may be estimated as the difference between outsourcing a task and performing it in-house (Dunlop, 2004). Through maintenance externalization, a set of advantages are obtained for the client, namely: (i) best maintenance practices due to expertise of the providers and the use of the latest maintenance technology, (ii) risk mitigation of high costs by setting for-purpose service contracts, (iii) reducing of capital investments, and (iv) in-house managers can spend more time in the strategic aspects of the business. On the contrary, some disadvantages are: (i) cost of contracting scarce services, making it possible to increase monopolistic behavior from the contractor, (ii) a potentially risky dependency, *e.g.*, control of machine availability transferred to a contractor, (iii) loss of corporative know-how, and (iv) the need to supervise the attainment of contract goals (and corresponding conflicts in case of non-performance) and to manage external resources (Jackson & Pascual, 2008). This last issue is critical since employees reporting may cause conflicts between the contractor and the client. Employees technically report to the contractor, but in fact, they are often under direct control of the client (Kumar, 2008). Possible litigation problems may also arise in the service sourcing relationship, for example, an accident involving contractors (Cawley, 2003). The optimal profile of risk implies a practical offsetting of operational risks and litigation risks (Dunlop, 2004).

A potential side product of outsourcing is backsourcing. It refers to the internalization process after the outsourcing has failed. Whitten and Leidner (2006) show that although the choice to outsource has been exhaustively considered by researchers, the decision to backsource has not received equal attention. According to them, product quality, service quality, relationship quality, and switching costs are variables related to the decision to implement backsourcing. Likewise, internal strategic guidelines of organizations also have an effect on the decision to backsource. Wong and Jaya (2008) suggests that service sourcing strategies can be influenced by power and politics at top level management, because managers have different experiences, backgrounds, philosophies, and knowledge, which may impact the decision-making process.

The existence of poorly defined contracts often produces a difference between the service level delivered by contractors and the performance expected by clients. This gap may become an important factor to consider when choosing between in-house or outsourcing (Wong & Jaya, 2008). Tseng, Tang, Moskowitz, and Plante (2009) point out that services provided by contractors should be explicit in maintenance contracts conditions in order to avoid unilateral decisions by contractors or clients. Tseng *et al* state that this specification creates a certain rigidity of contractual terms, and factors such as scheduling of maintenance activities or flexibility for adopting new technologies have an impact on maintenance outsourcing coordination. In the current increasing competitive industry scenario, effective channel coordination has become crucial; which has attracted the interest of numerous empirical and theoretical studies (Tarakci et al., 2006a). The situation highlights the need for designing performance-based contracts to achieve a win-win coordination for clients and contractors at the same time; namely, a channel coordination.

Desired channel coordination is relevant not only to for-profit companies, but also to service-oriented organizations. Non-profit organizations have some characteristics that differentiate them from the profit-centered companies, including: (i) non-profit organizations do not have owners, (ii) these firms are not allowed to make a profit, and (iii) many of these organizations have tax privileges (Glaeser, 2002). The focus of non-profit organizations is on achieving a high service-level. An example of this situation, it may be found in defense industry, where the equipment availability is critical to provide dissuasive power to the country.

Having introduced the relevance of maintenance outsourcing, its specific drivers and border conditions, and the need for contracts to attain channel coordination, the rest of the chapter is structured as follows. Section 5.1 shows the problem formulation noting the implications of imperfect maintenance and finite-horizon service contracts. The model formulation is explained in Section 5.2. Section 5.3 presents the coordination mechanisms for profit centered clients. Section 5.4 describes the case of non-profit centered clients. Finally, Section 5.5 provides the conclusions of the work.

5.1 Problem formulation

Coordination in the supply chain, *i.e.* channel coordination, plays a relevant role on outsourcing. In the current dynamic environment, coordination of the parties is essential for services in the chain. Kumar (2001) suggests that two types of coordination are necessary in supply chain management: horizontal coordination (between the players who belong to the related industry) and vertical coordination (across industry and companies). Although the need for coordination is becoming increasingly evident, efforts to create infrastructures to enact such coordination are still in their early stages. Kumar states that supply chains can create systems that integrate instant visibility and whole dynamic supply chains on an as-needed basis. Those chains are more likely to reach competitive advantages over those that do not adopt such systems (Kumar, 2001).

There are several methods to achieve cooperation among a client and a contractor. A common practice is to use a *work package contract* which specifies a maintenance strategy and a cost structure that leads the contractor to accept the deal. This kind of contract falls into the category of *labor plus parts*, in which the contractor sees no incentives to improve its performance (Tarakci et al., 2006a), as the more its services are required, the more the contractor earns. For the contractor, the usual focus is to keep customer loyalty by showing capability to outperform competitors (Egemen & Mohamed, 2006).

Another aspect to take into account when negotiating contracts is the system level at which the contract acts on a system. The contract may include the maintenance of (usually) a single component of a complex system and can also be an umbrella or full service contract considering the whole system. An example of the first case is presented by Tarakci et al. (2006a). The same authors study a manufacturing system with multiple processes where each component is maintained independently (Tarakci et al., 2006b).

Considering the need for reaching effective coordination of the supply chain, Tarakci et al. (2006a) study incentives to maximize the total profit of the service chain. Namely, contracts which aims to achieve a win-win coordination to maximize the profits of the actors. According to Tarakci et al. (2006a), these contracts lead the contractor to improve the performance of maintenance operations. They demonstrate that this kind of contracts can be an effective tool to achieve the desired overall coordination. Nevertheless, they consider both perfect maintenance for preventive actions and infinite horizon contracts. These two limitations do not seem to make a realistic condition for a full implementation of the model in the operational reality.

The inclusion of imperfect maintenance contributes to a realistic modeling of system failure rates. Changes in failure patterns strongly influence maintenance and replacement decisions (Pascual & Ortega, 2006). Perfect maintenance contemplates that every maintenance action returns the system to its “as good as new” condition. However, Malik (1979) points out that working systems under wear-out failures are not expected to be restored to a new condition, and proposes the inclusion of a maintenance improvement factor for imperfect repairs. Furthermore, Nakagawa (1979) suggests that failure rate functions on imperfect maintenance cases could be adjusted using a probability approach; thus, the action is perfect (“as good as new”) with probability (1-α) and minimal (“as bad as old”) with probability α. Zhang and Jardine (1998) argue that enhancements by overhauls tend to be magnified by Nakagawa’s model and there is a possibility that the failure rate could be bounded; consequently, the appropriateness of the model could be restrained. Zhang and Jardine present an optional approach in which the system failure rate function is in a dynamic modification between overhaul period, since this rate is considered between “as bad as old” and “as good as previous overhaul period” using a fixed degree. Zhang and Jardine’s approach is used in the model formulation of the present paper. Due to imperfect maintenance sets the system failure rate between a new condition and a previous to failure condition (Pham & Wang, 1996), the incorporation of this realistic assumption is fundamental for model applicability.

An important aspect that should be considered during the coordination process is the time-horizon of the contracts. This condition does not only hold because the amortization of investments by the provider but also because the assets under consideration suffer in general an aging process that increases the need to perform maintenance and overhaul actions. Regarding this, Lugtigheid et al. (2007) focus on finite-horizon service contracts. They note the lack of literature for finite-horizon contracts, and present several methods and consider repair/replacement for critical components. In our case, the focus is not on component level, but on system level. Complementarily, Nakagawa and Mizutani (2009) propose finite-interval versions for classic replacement models, such as models of periodic replacement with minimal repair, block replacement and simple replacement. Regarding the aging process is often an effect of imperfect maintenance practices that can be modeled using different approaches, many of them described in references such as Wang (2002); Li and Shaked (2003); Nicolai and Dekker (2008). Nakagawa and Mizutani (2009) also consider imperfect maintenance models but do not split costs into in-house and outsourcing costs. In this article we focus on the well known method described by Zhang and Jardine (1998), but the reach of the concepts to other approaches like virtual age models (Kijima, 1989) is straightforward.

5.2 Model formulation

Let us consider an equipment whose maintenance the client wishes to subcontract. According to clients own needs, and considering the service supply chain benefits, he intends to offer a contract that: (i) maximizes the sum of expected profits for the parties along the duration of the contract, (ii) minimizes his maintenance costs subject to a service level constraint. The first situation may appear when both parties are profit-centered (i.e. a mine site and a haul-truck maintenance contractor). In the second case, the client is committed to obtain a given service level and intends to minimize the maintenance costs while the contractor is profit-centered (i.e. a hospital and the critical equipment maintenance contractor).

For tractability of analyses, we limit to consider the following conditions:

1. The system failure rate function follows a Weibull distribution with shape parameter β (integer) and
$$\beta > 1. \tag{5.1}$$
2. A preventive maintenance action restores the system to *almost as good as new* condition (Zhang & Jardine, 1998) as follows
$$\lambda_k(t) = \alpha\lambda_{k-1}(t-T) + (1-\alpha)\lambda_{k-1}(t), \tag{5.2}$$
where t represents time, k corresponds to the index of the k-th preventive action, and α is the maintenance improvement factor with $0 \leq \alpha \leq 1$.
3. Corrective maintenance is *minimal*.
4. Direct (spare+labour) costs and durations of preventive maintenance are C_p (monetary units, mu) and T_p (time units, tu), respectively.
5. Direct costs and durations of corrective maintenance are, correspondingly, C_r (mu) and T_r (tu).
6. The interval between preventive maintenance is T (tu).
7. The contractor is free to select the age T at which he will perform preventive maintenance.
8. The basic service fee is p (mu/tu).

Table 5-1: κ vs n

β	κ
1	n
2	$n^2(1-\alpha)+n\alpha$
3	$n(n-1)(n-2)(1-\alpha)^2+3n(n-1)(1-\alpha)+n$

9. The contractor sets a minimum expected profit π (mu/tu) to participate in the game.
10. The net revenue of the client after production costs is R (mu/tu).
11. The contract lasts from the beginning of a system life-cycle to the end of the n-th overhaul.

Before the first preventive maintenance the failure rate is

$$\lambda(t) = \lambda_0 \beta t^{\beta-1}, t < T. \tag{5.3}$$

The expected number of failures N, after n overhauls is

$$N(nT) = \sum_{i=0}^{n} \left(\begin{array}{c} n \\ i \end{array} \right) \alpha^{n-i}(1-\alpha)^{i-1} N_0(iT), \tag{5.4}$$

where $N_0 = \int_0^{nT} \lambda(t)dt$.

For $n \geq \beta$ and β integer, the expected number of failures is

$$N(nT) = \kappa \lambda_0 T^{\beta},$$

where κ depends on α and n. Some values are shown in Table 5-1.

The expected interval availability during the contract is

$$A(nT) = \frac{nT - N(nT)T_r}{n\left(T + T_p\right)}, \tag{5.5}$$

and the expected profit for the buyer is

$$\Pi_m(nT) = RA(nT) - p. \tag{5.6}$$

The expected maintenance (direct) costs are

$$c_i(nT) = \frac{nC_p + N(nT)C_r}{n\left(T + T_p\right)}, \tag{5.7}$$

which leads to the expected contractor profit

$$\Pi_c(nT) = p - c_i(nT). \tag{5.8}$$

Following the lead of Tarakci et al. (2006a),when Equations (5.6) and (5.8) are compared for a fixed fee p, it is clear that the client wishes to maximize availability (which is equal to utilization in our case), while the contractor wishes to minimize maintenance costs. It is necessary to propose a contract to achieve collaboration for both parties. With that in mind, the expected profit of the service chain is

$$\Pi(nT) = RA(nT) - c_i(nT). \tag{5.9}$$

To achieve channel coordination it is necessary to maximize $\Pi(nT)$, however, this situation hardly ever will be reached if both the client and the contractor try to maximize their own objective functions, as shown in the following Lemma.

Lemma 5.1. *Define*

$$g_\alpha(T) = \kappa\lambda_0\left(\left(\beta - 1\right)T^\beta + \beta T_p T^{\beta-1}\right) \tag{5.10}$$

Then,

1. *The optimal solution that maximizes the client's profit is T_m^*, which satisfies:*

$$g_\alpha(T_m^*) = n\frac{T_p}{T_r} \tag{5.11}$$

2. *The optimal solution that maximizes the contractor's profit is T_c^*, which satisfies:*

$$g_\alpha(T_c^*) = n\frac{C_p}{C_r} \tag{5.12}$$

3. *The optimal solution that maximizes the total profit is T^*, which satisfies:*

$$g_\alpha(T^*) = n\frac{RT_p + C_p}{RT_r + C_r} \tag{5.13}$$

This result is equivalent to the one developed by Tarakci et al. (2006a); however, some significant differences exist between both results. Note that the definition of $g_\alpha(T)$ differs from the definition of $g(T)$ proposed by Tarakci *et al.* in a κ factor which depends on both n and α. This factor is important, as it takes into account that the contract has a finite time horizon and that overhauls don't leave the system in a *as good as new* condition.

With the following Lemmas, we discuss the dependence of the function $g_\alpha(T)$ on model's constants and the effect of finite time horizon and imperfect maintenance hypothesis in the setting of optimal preventive maintenance (PM) intervals.

Lemma 5.2. *In ceteris paribus condition:*

1. *The optimal maintenance intervals for the client, the contractor, and the service chain decrease in the scale and shape parameters of process failure-rate function.*

2. *The optimal PM interval T_m^* for the client increases in the PM time T_p, but that of the contractor (T_c^*) decreases in PM time.*

Lemma 5.2 is completely analogous to the one proved by Tarakci *et al.*, and it shows the same intuitive facts for our case; if there is a higher process deterioration rate, more frequent overhauls would be necessary from the point of view of all players. However, if an improvement in the PM time is made for the contractor, the effect on optimal times will be opposite for the parties, and channel coordination will be more difficult to reach.

On other hand, in a first analysis of Equations (5.11), (5.12) and (5.13), it would appear that if n is increased, then the optimal intervals will be increased. This observation is not valid, because g_α is a function that depends on n, so it is not straightforward how variations on n affects the value of optimal PM intervals.

The following Lemmas show an interesting relationship between $\kappa(\alpha, n)$ and n, which allow us to understand the dependence of the optimal PM intervals on contract's horizon time.

Lemma 5.3. *Let*

$$\kappa(\alpha, n) = \sum_{i=0}^{n} \binom{n}{i} \alpha^{n-i}(1-\alpha)^{i-1} i^{\beta} \tag{5.14}$$

$\alpha \in [0, 1]$, $\beta \geq 1$ *and* $n \in \mathbb{N}$*, then:*

$$\kappa(\alpha, n) \geq n \tag{5.15}$$

Lemma 5.4. *Let $n, i \in \mathbb{N}$, $n \geq i$, $\beta \in \mathbb{R}$, $\beta \geq 1$, then:*

$$\left(n\binom{n+1}{i} - (n+1)\binom{n}{i}\right) i^{\beta} \geq (n+1)\binom{n}{i-1}(i-1)^{\beta} \tag{5.16}$$

Lemma 5.5. *Let $\alpha \in [0,1]$, $\beta \geq 1$ and $n \in \mathbb{N}$, then:*

$$\frac{n}{\kappa(\alpha,n)} \geq \frac{n+1}{\kappa(\alpha,n+1)} \tag{5.17}$$

Tarakci et al. (2006a) showed that the optimal PM intervals, assuming an infinite time horizon and a renewal process, were given by

$$g(T^*_{m_{rp}}) = \frac{T_p}{T_r}, \tag{5.18}$$

$$g(T^*_{c_{rp}}) = \frac{C_p}{C_r}, \tag{5.19}$$

$$g(T^*_{rp}) = \frac{RT_p + C_p}{RT_r + C_r}. \tag{5.20}$$

According to their definitions, g_α and g are related as follows

$$g_\alpha(T) = \kappa(\alpha,n)g(T). \tag{5.21}$$

Hence, we can re-write optimality conditions of Lemma 5.1 in terms of $g(T)$

$$g(T^*_{m_{n+1}}) = \frac{n+1}{\kappa(\alpha,n+1)}\frac{T_p}{T_r} \leq g(T^*_{m_n}) = \frac{n}{\kappa(\alpha,n)}\frac{T_p}{T_r} \leq \frac{T_p}{T_r} = g(T^*_{m_{rp}}), \tag{5.22}$$

$$g(T^*_{c_{n+1}}) = \frac{n+1}{\kappa(\alpha, n+1)} \frac{C_p}{C_r} \leq g(T^*_{c_n}) = \frac{n}{\kappa(\alpha, n)} \frac{C_p}{C_r} \leq \frac{C_p}{C_r} = g(T^*_{c_{rp}}), \tag{5.23}$$

$$\begin{aligned} g(T^*_{n+1}) &= \frac{n+1}{\kappa(\alpha, n+1)} \frac{RT_p + C_p}{RT_r + C_r} \leq g(T^*_n) \\ &= \frac{n}{\kappa(\alpha, n)} \frac{RT_p + C_p}{RT_r + C_r} \leq \frac{RT_p + C_p}{RT_r + C_r} = g(T^*_{rp}). \end{aligned} \tag{5.24}$$

Inequalities in Equations (5.22), (5.23), (5.24) follow from Lemmas 3, 4 and 5. As $g(T)$ is an increasing function, it is straightforward that optimal PM intervals for finite horizon contracts are smaller or equal than optimal PM intervals for an infinite horizon contract, in *ceteris paribus* condition. Even more, PM intervals will be smaller in contracts with more periods agreed, i.e., only because the contract is longer we have to do more preventive maintenance.

On the other hand, considering the $\kappa(\alpha, n)$ definition, we can notice that a lower α lets to increase κ. This result is very intuitive, since a low improvement in failure rate after an overhauling creates incentives to do PM more often.

Moreover, it is straightforward to prove that

$$\lim_{\alpha \to 1} \kappa(\alpha, n) = \lim_{\alpha \to 1} \sum_{i=0}^{n} \binom{n}{i} \alpha^{n-i} (1-\alpha)^{i-1} i^{\beta} = n. \tag{5.25}$$

Thus, looking at Equations (5.22), (5.23) and (5.24) we can conclude that if perfect overhauls are performed, (renewal process) optimal conditions will not depend on n, then the decisions over PM intervals will not depend on contract time horizon.

Since all right hand expressions in optimal PM interval condition in Equations (5.22), (5.23), (5.24) are weighed by $n/\kappa(\alpha, n)$, which does not depend on T, Lemma 3 of Tarakci et al. (2006a) is applicable. It allow us to state an analogous Lemma.

Lemma 5.6. *The relationships among the optimal PM intervals for the client, the contractor, and the service chain are given by: (i)* $T_c^* = T_m^* = T^*$ *if* $C_p/C_r = T_p/T_r$*; (ii)* $T_c^* > T^* > T_m^*$ *if* $C_p/C_r > T_p/T_r$*; and (iii)* $T_c^* < T^* < T_m^*$ *if* $C_p/C_r < T_p/T_r$*.*

5.3 Coordination mechanisms for profit centered clients

The following sections define both the cost subsidization contract and uptime target and bonus contract for profit centered clients. Lastly, a corresponding case study is developed.

5.3.1 The cost subsidization contract

Basis for establishing the Cost Subsidization contract is given by Tarakci et al. (2006a). If $T_c^* > T^*$, the client agrees to subsidize the cost of the preventive maintenance in order to make them more attractive for the contractor, who wishes to maximize his profit. Let ΔC_p be that bonus, then, the effective cost observed by the contractor of a preventive maintenance is

$$C_p' = C_p - \Delta C_p. \tag{5.26}$$

In order to obtain $T_c^{*'} = T^*$ we know that

$$g_\alpha(T^*) = n\frac{RT_p + C_p}{RT_r + C_r} = n\frac{C_p'}{C_r} = g_\alpha(T_c^{*'}), \tag{5.27}$$

then

$$C_p' = C_r\frac{RT_p + C_p}{RT_r + C_r}, \tag{5.28}$$

and

$$\Delta C_p = C_p - C'_p. \tag{5.29}$$

The result showed by Equation (5.28) is remarkable, because it is exactly the same than the one obtained for infinite time contracts with renewal process failure.

The expected profit for the contractor is now

$$\Pi_c(nT) = p - c_i(nT) + \frac{n\Delta C_p}{n(T+T_p)} = p - c_i(nT) + \frac{\Delta C_p}{T+T_p}, \tag{5.30}$$

and for the client

$$\Pi_m(nT) = RA(nT) - p - \frac{n\Delta C_p}{n(T+T_p)} = RA(nT) - p - \frac{\Delta C_p}{T+T_p}. \tag{5.31}$$

Lemma 5.7. *Channel coordination can be achieved using Cost Subsidization contract with $p \in [p_1, p_2]$, where:*

$$p_1 = \pi + c_i(nT^*) - \frac{\Delta C_p}{T^*+T_p} \geq 0 \tag{5.32}$$

$$p_2 = RA(nT^*) + \pi - \Pi(nT_c^*) - \frac{\Delta C_p}{T^*+T_p} \geq p_1 \tag{5.33}$$

If $T_c^* < T^*$, the client agrees to subsidize the cost of the corrective maintenance in order to make them more attractive for the contractor, who wishes to maximize his profit. Let ΔC_r be that bonus, then, the effective cost observed by the contractor of a preventive maintenance is

$$C_r' = C_r - \Delta C_r. \tag{5.34}$$

In order to obtain $T_c^{*'} = T^*$ we know that

$$g_\alpha(T^*) = n\frac{RT_p + C_p}{RT_r + C_r} = n\frac{C_p}{C_r'} = g_\alpha(T_c^{*'}), \tag{5.35}$$

then

$$C_r' = C_p\frac{RT_r + C_r}{RT_p + C_p}, \tag{5.36}$$

and

$$\Delta C_r = C_r - C_r'. \tag{5.37}$$

The expected profit for the contractor is now

$$\Pi_c(nT) = p - c_i(nT) + \frac{N(nT)\Delta C_r}{n(T+T_p)}, \tag{5.38}$$

and for the client

$$\Pi_m(nT) = RA(nT) - p - \frac{N(nT)\Delta C_r}{n(T+T_p)}. \tag{5.39}$$

Lemma 5.8. *Channel coordination can be achieved using Cost Subsidization contract with* $p \in [p_1, p_2]$*, where:*

$$p_1 = \pi + c_i(nT^*) - \frac{N(nT^*)\Delta C_r}{n(T^*+T_p)} \geq 0 \tag{5.40}$$

$$p_2 = RA(nT^*) + \pi - \Pi(nT_c^*) - \frac{N(nT^*)\Delta C_r}{n(T^*+T_p)} \geq p_1 \tag{5.41}$$

5.3.2 The Uptime Target and Bonus (UTB) contract

Basis for establishing the UTB contract is given by Tarakci et al. (2006a). If the contractor achieves an uptime level above a target uptime τ, the client agrees to increase the contract attractiveness by a per-unit-time bonus B. Both contractor's profit and client's profit respectively become:

$$\Pi_c'(nT) = p - c_i(nT) + B[A(nT) - \tau]^+, \tag{5.42}$$

where $[x]^+ = \max\{x, 0\}$,

$$\Pi_m'(nT) = RA(nT) - p - B[A(nT) - \tau]^+. \tag{5.43}$$

Thus, the client selects B, τ, and p, in order to incentive the contractor chooses the interval T^* to maximize the profit $\Pi_c'(nT)$. In this case, the channel coordination is set by the following Lemma.

Lemma 5.9. *Channel coordination can be achieved using UTB contract with $\tau \in [\tau_1, \tau_2]$ and $p \in [p_1, p_2]$, where:*

$$\tau_1 = \frac{\Pi(nT^*) - \pi}{R} \tag{5.44}$$

$$\tau_2 = A(nT^*) - \frac{c_i(nT^*) - c_i(nT_c^*)}{R} \tag{5.45}$$

$$p_1 = R\tau + \pi - \Pi(nT^*) \tag{5.46}$$

$$p_2 = R\tau + \pi - \Pi(nT_c^*) \tag{5.47}$$

Table 5-2: Initial parameters

Parameter	Value
λ_0	0.001
β	3
T_p	1
T_r	0.30
C_p	8
C_r	0.40
R	15
p	2.50
π	2.50
α	0.90
n	5

5.3.3 Case study

Let us consider a customized version of the case described by Tarakci et al. (2006a). Parameter values are shown in Table 5-2. We are interested in a study of the optimal interval T for contractor, client and service chain, respectively. Figure 5-1 displays such values in terms of $g_\alpha(T)$, whereas Figure 5-2 exhibits a study of κ in terms of β and n. In summary, Table 5-3 shows results for this initial case. Figure 5-3 and Figure 5-4 show a study of availability in terms of T, and the expected profits, respectively. Then, the optimal duration of the contract is: $n(T^* + T_p) = 5(9.56 + 1) = 52.80$.

When the optimal PM interval (T^*) is set, then the fee p to be adopted by the client for satisfying the contractor's minimum expected profit, i.e., the equilibrium service fee, is: 3.33. If Π_c is below π, as this case with: $p = 2.50$,

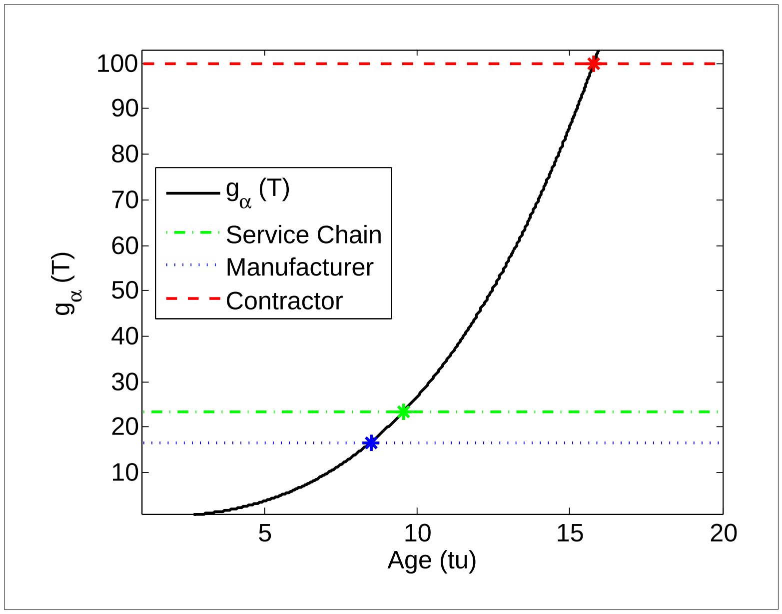

Figure 5-1: Study of $g_\alpha(T)$ for $n = 5$, where $*$ indicates each optimal value

Table 5-3: No incentives. Results.

	T	A	Π	Π_m	Π_c
T_m^*	8.48	0.850		10.21	
T^*	9.56	0.848	11.88		
T_c^*	15.79	0.777			1.67

then the contractor does not respond to that profit. Hence, it is necessary to seek ways to motivate.

Because of $T_c^* > T^*$, it turns necessary to enlarge the PM frequency made by the contractor. Considering the previous example, now the interest is in finding a bonus ΔC_p, which sets the optimal point for the contractor with the one of the service chain. As shown in Table 5-3, this point is located at: $T^* = 9.56$.

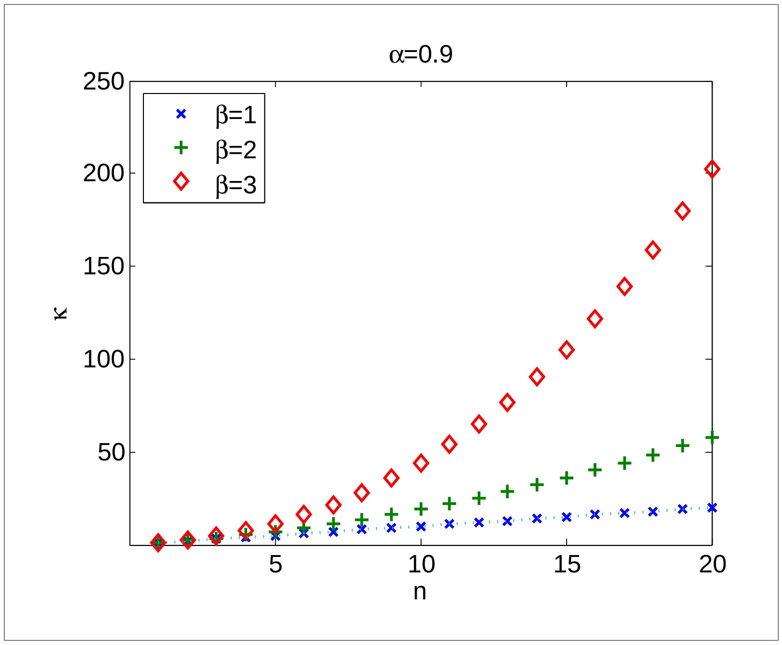

Figure 5-2: Study of κ

Evaluating Equation (5.29) it is possible to calculate the bonus, then

$$\Delta C_p = 6.12 \ .$$

Figure 5-5 shows an study of the profits for both parties (Equations (5.30) and (5.31) as a function of T). Note that even if the bonus is obtained, the contractor still does not respond as the expected profit is below π. Utilizing Equations (5.32) and 5.33, the limits for the service fee are: $p_1 = 2.75$ and $p_2 = 3.67$. Following the lead of Tarakci et al. (2006a), the extra profit from channel coordination is the difference between p_2 and p_1, which in this case is: 0.92. This can be distributed between the contractor and the client by choosing p ($p \in [p_1, p_2]$). For example, if p is set at: 3.30, then the contractor's profit is: 3.05 (greater than the contractor's minimum expected profit), and the client's profit is: 8.84. In these conditions, the contractor receives an incentive for entering to the coordination process. The sensitivity of this calculation is

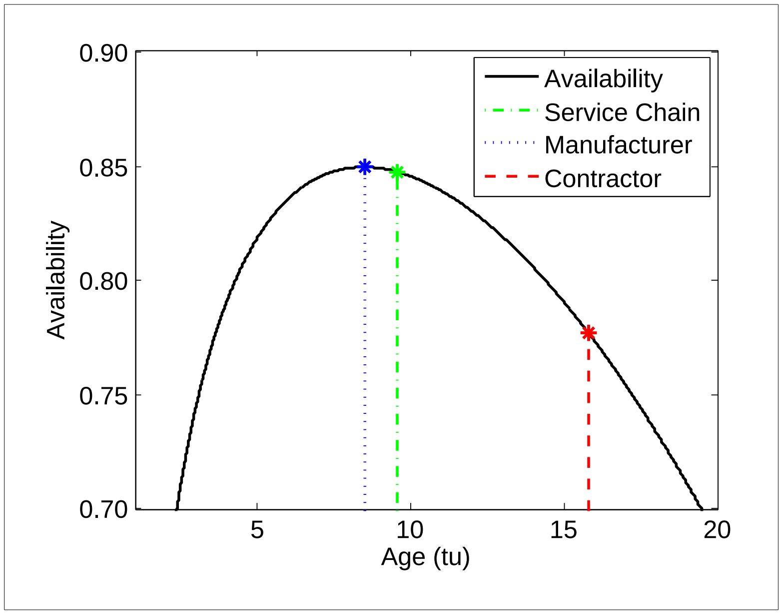

Figure 5-3: Study of A, where $*$ indicates each optimal value

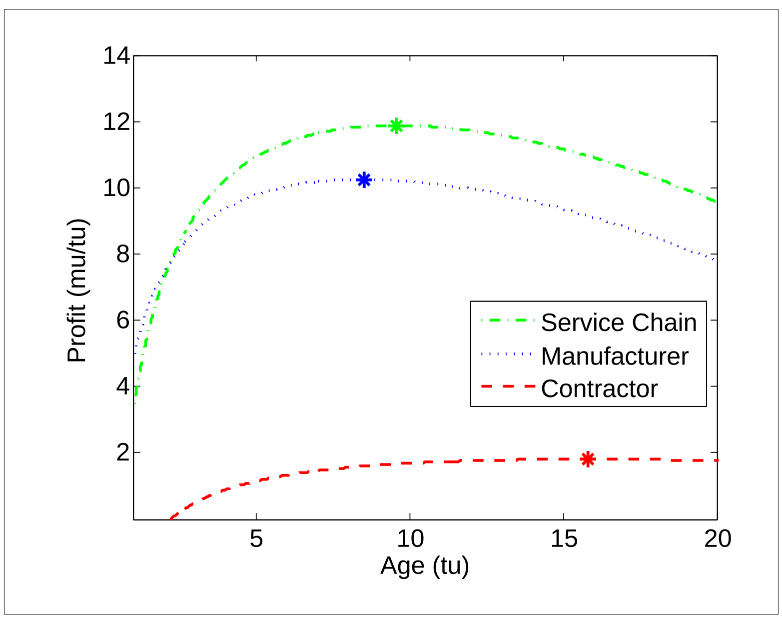

Figure 5-4: Study of the expected profits

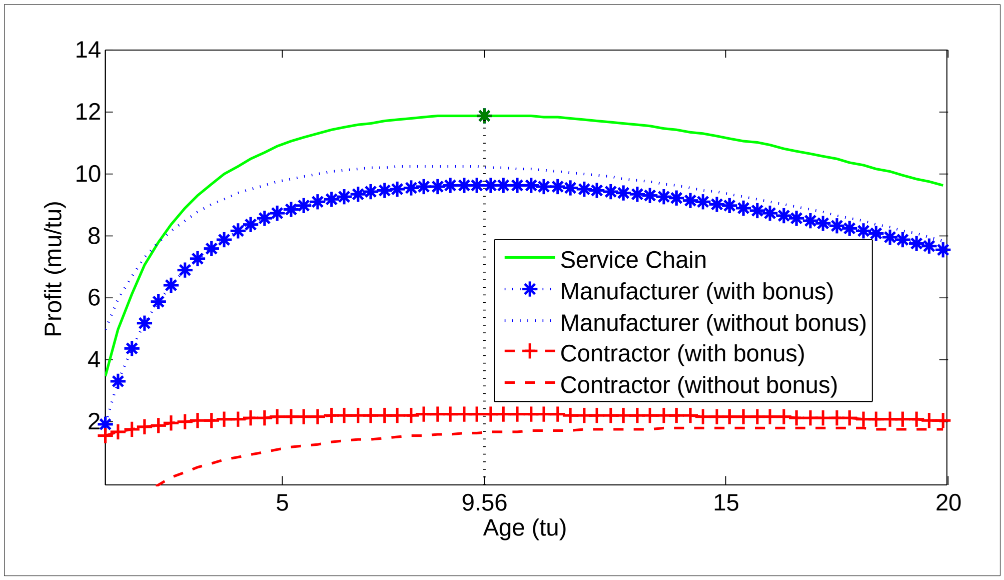

Figure 5-5: Expected profits in terms of T with bonus for preventive actions

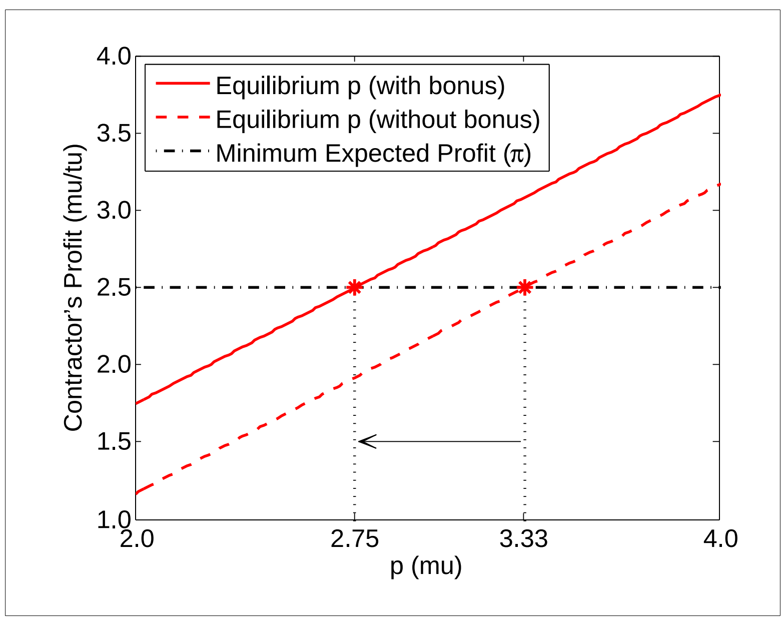

Figure 5-6: Decreasing of equilibrium service fee

shown by Figure 5-6, where the equilibrium service fee decreases because the incentive given by cost subsidization.

5.4 Non-profit centered clients

In several organizations (military, public services, etc.), the main interest is to provide a contracted service level (i.e., availability or dissuasive power) at minimum direct cost. In general, a reference value is set (from benchmarks with similar organizations abroad or just imposed) and/or because budget or capacity constraints. Let us consider the case where A_r is the reference availability. Notice that the client is interested in achieving the contracted service level, in order to obtain an achievable profit for its own benefit and for the contractor as well.

5.4.1 Bonus to preventive actions

Let $T^*_{m_2}$ be the interval that achieves

$$A(T^*_{m_2}) = A_r.$$

A_r should be feasible, then, a necessary condition is

$$A_r \leq max(A). \tag{5.48}$$

Note that the client only needs to give the bonus to the contractor if $T^*_{m_2} \leq T^*_c$. Otherwise, the contractor is already working on the interval; therefore, the client does not have to provide the incentive. Depending on the cost ratios, it is needed to evaluate the potentially feasible solutions according to roots of

$$\kappa\lambda_0 T_r T^\beta + (A_r - 1)\, nT + A_r n T_p = 0. \tag{5.49}$$

If the left-hand side of the above equation is considered, it is efficiently reasonable to choose the largest T that achieves A_r. To provide an incentive

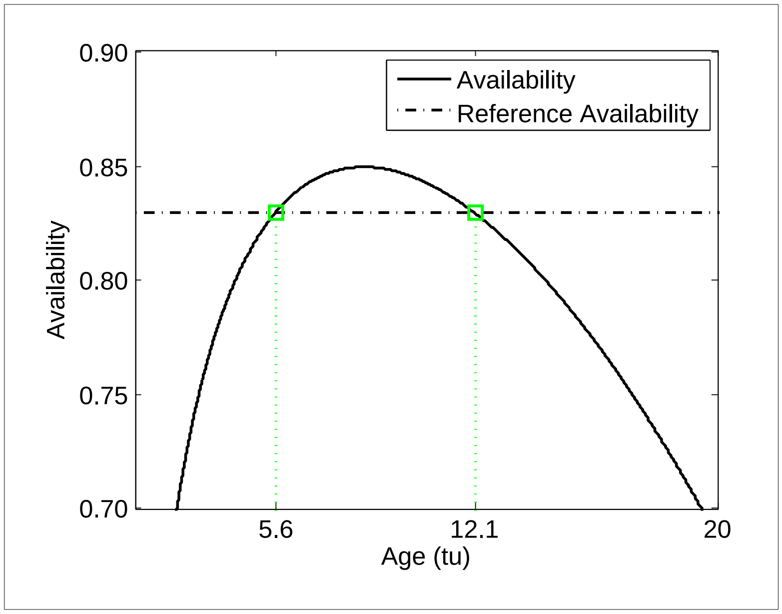

Figure 5-7: Potential solutions by setting $A_r = 0.83$

for the contractor to set $T = T^*_{m_2}$, he must perceive a C''_p such that

$$n\frac{C''_p}{C_r} = g_\alpha(T^*_{m_2}), \tag{5.50}$$

which allows to set the incentive at

$$\Delta C_p = C_p - C''_p. \tag{5.51}$$

5.4.2 Case study

Let us consider the case previously analyzed. The client has set its reference availability at: $A_r = 0.83$. If Equation (5.49) is evaluated, then two potential solutions appear:

$$T_1 = 5.60 \quad \text{and} \quad T_2 = 12.05.$$

These potential solutions can be seen on the Figure 5-7. If both solutions are evaluated in Equations (5.50) and (5.51), two different bonuses are obtained. For the sake of generality, the following example is enunciated. If the service level is set at the contractor's availability, namely: $A_r = 0.777$, the two potential solutions for T are: $T_a = 3.64$ and $T_b = 15.79$. Respectively, potential bonuses are: $\Delta C_{pa} = 7.87$ and $\Delta C_{pb} = 0$. In spite of two numerical solutions for achieving the same A_r, if PM interval is set as equal as the contractor's interval, there is no necessity of any incentive. Expectedly in these circumstances, the largest solution for T is the most economically suitable.

Due to the largest T achieves the identical desired availability with the lowest cost for the client, the most efficient option is estimating the bonus (ΔC_p) using: $T_2 = 12.05$. Then

$$\Delta C_p = 4.34. \tag{5.52}$$

In the same way, if the client fixes the feasible maximum availability like a target, namely when: $A_r = 0.8497$, then: $T^*_{m_2} = 8.48$ (the same as T^*_m). But in this case C''_p is: 1.33, and the client must pay a bonus of: 6.67 for each preventive action. This result is consequent with the bigger challenge for increasing the service level. Finally, Figure 5-8 shows the rising of the contractor's profit from a no incentive contract to a bonus to preventive actions contract.

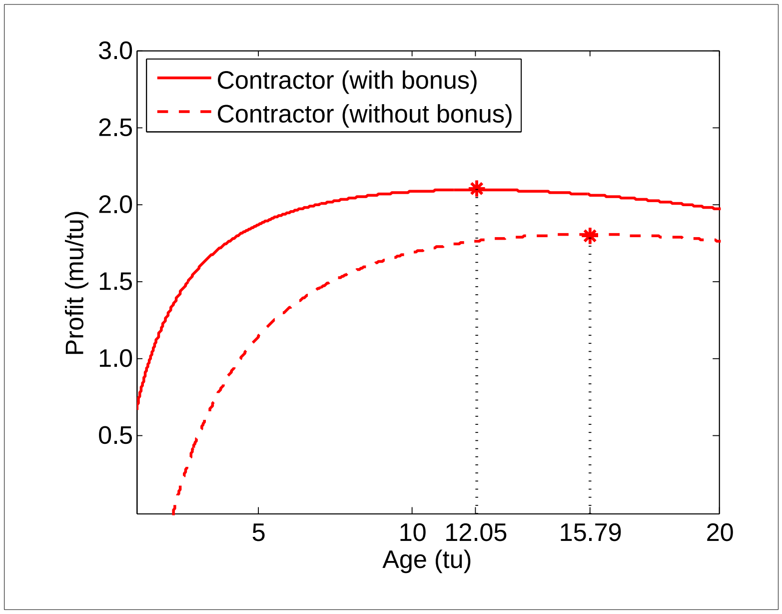

Figure 5-8: Profit for the contractor by setting the feasible maximum availability

5.5 Conclusions

This article introduces a model that defines contractual conditions to coordinate the supply chain. This is achieved by setting a preventive maintenance strategy that maximizes the total expected profit for clients and contractors, who usually try to optimize their profits separately. In particular, the method finds the optimal interval between preventive maintenance for the contractor, client and service chain, correspondingly. The study extended previous works by considering imperfect maintenance and finite-horizon service contracts, and also shows how these affect stakeholder's decision-making. Previous works have been extended to consider not only profit-centered clients, but also non-profit centered clients. We have evaluated how to achieve the desired supply channel coordination. In order to encourage both players to optimize their actions altogether and thus achieving the increase of their expected profits.

In the profit-centered clients case, we have found the optimal duration of the contract which reaches channel coordination. However, there are scenarios where the expected profit for the contractor is not enough to drive changes in his preventive maintenance interval. One way to motivate him is that the client pays a bonus for each preventive maintenance made by the contractor, provided that interventions enable to achieve the supply chain optimization. We estimated such bonus.

For non-profit centered clients, we evaluated the optimal interval to achieve a reference availability delivered by the client. Again, we offer a bonus that motivates the contractor to achieve the desired availability, maximizing profits for himself and the entire supply chain.

Finally, we demonstrated that the model achieves win-win coordination of the supply chain. Client and contractor are encouraged to improve continually their maintenance services, as profits increase with respect to those obtained when no coordination occurs.

6. A DECISION-MAKING FRAMEWORK TO INTEGRATE MAINTENANCE CONTRACT CONDITIONS WITH CRITICAL SPARES MANAGEMENT

The best result will come from everyone doing what is best for himself and the group.
— JOHN NASH

Maintenance outsourcing is a strategic means to improve business performance. Outsourcing creates value through the use of external resources by and for companies to acquire and sustain competitiveness (Arnold, 2000). The maintenance function is a main driver of outsourcing since it has excellent potential to achieve cost benefits and enhance performance among partners (Kumar, 2008). This business purpose is meaningful for asset intensive industries –such as Mining, Aeronautic, or Defense– which face substantial investment in maintaining complex equipment and high demand on system availability. For these firms, the main reasons to contract out maintenance tasks rather than perform them in-house are focusing on core business, accessing highly specialized services at competitive costs, and sharing risks (Kumar, 2008; Tarakci et al., 2006a; Pascual et al., 2012; Jackson & Pascual, 2008). When dealing with outsourcing, effective supply chain coordination allows achieving a rewarding situation for all stakeholders (Tarakci et al., 2006a). Accordingly, a model capable of coordinately optimizing performance can lead to successful maintenance contracting strategies in capital intensive environments.

Spare parts management has a critical role toward operational efficiency of asset intensive industries. Equipment criticality is defined by the most relevant assets that efficiently and safely sustain production (Dekker et al., 1998). The operation of such equipment is consequently supported by critical spare parts (Louit, 2007). Major spare components are related to considerable investment, high reliability requirements, extended lead times, and plant shutdowns with important effects on operational continuity (Godoy et al., 2013). A method to prevent production loss events is having inventories at hand, especially when either target service levels or backorder penalties are large (Glasserman, 1997). This is the case of capital intensive firms, wherein critical spares storage is directly linked to business success due to the impact of stock-outs on assets utilization (Louit, 2007). As an example, the aviation supply chain holds a remarkable US$ 50 billion in spares inventories to provide availability service (Kilpi & Vepsäläinen, 2004). Efficient critical spares stockholding is therefore essential for companies in which success strongly depends on equipment performance.

Maintenance contracts profitability can be significantly affected by critical spares policies. Particularly, the stock of critical repairable spares can be interpreted as a pool of components from where replacements are satisfied (Louit, 2007). Consistently with the serious impact on operational and financial performance, managing the pool of critical spare components becomes a key to improve profits within the service contract. Nevertheless, as it depends on the decision-maker's position, both supply chain parties –service receiver (client) and external provider (agent)– traditionally intend to maximize benefits separately. If the client controls the spare parts pool, there are scarce incentives for the provider to avoid an indiscriminate use of components aside from regular restraints. Conversely, if the agent administers the pool, rational use of components turns reasonable. Critical spares stockholding is a supply chain lever to keep maintenance outsourcing viable for the parties involved.

In order to coordinate the contracting parties, we investigated whether or not the client should outsource the management of the pool of spare components to the agent. This paper provides a decision-making framework to profitably integrate the contractual maintenance strategy with critical spares stockholding. The scheme is based on a joint value –preventive interval and stock level– that maximizes the supply chain returns whilst evaluating the impact of an additional part to stock. Using an imperfect maintenance strategy over a finite horizon, the model leads to an optimal decision to allocate the critical spare components pool within the outsourcing contract. An interesting link is thus created between maintenance performance indicators and supply chain practices.

Having introduced the importance of allocating critical spare parts management within maintenance service contracts for asset intensive industries, the rest of the paper is organized as follows. Section 6.1 states the differences between the enriched concept of the present paper and relevant existent researches. Section 6.2 describes the model formulation to integrate maintenance and spares supply indicators. Section 6.3 presents a case study within the Mining industry, which holds substantial spares inventories to ensure system performance. Finally, Section 6.4 provides the main implications of applying the joint model to coordinate the outsourcing strategy under an asset management perspective.

6.1 Literature review

The following literature review is structured as the importance of the management of the pool of critical spares within maintenance outsourcing contracts.

As an interesting strategy to achieve cost-benefits, consolidating inventory locations by cooperative pooling has been addressed by Kilpi and Vepsäläinen (2004); Lee (1987); Dada (1992); Benjaafar et al. (2005), among other studies. In the context of repairable spares pooling, the cost allocation problem is analyzed using game theoretic models by Wong et al. (2007). As recent implementations, a virtual pooled inventory by managing information systems is included in Braglia and Frosolini (2013) and a calculation model of spare parts demand, storage and purchase planning in the coal mining industry is reported by Qing he et al. (2011). When dealing with cooperation in contractual alliances, the study of Gulati (1995) states the relevance of interfirm trust to deter opportunistic behaviour in a shared ownership structure. Such trust is an important issue related to pooling strategies. A widely applied modeling for repairable items stockholding focused on system availability and spares investment is provided by Sherbrooke (2004). Since its accuracy to determine the optimal inventory levels for both single-site and multi-echelon techniques, the above-mentioned model is used to adapt the concept of spare service level in the present paper.

Maintenance outsourcing under supply chain coordination is discussed by Tarakci et al. (2006a), a study that deals with incentive contracts terms to coordinate agents and clients by a maintenance policy seeking to optimize the total profit. The work of Pascual et al. (2012) extends this approach by incorporating realistic conditions, such as imperfect maintenance and finite time-span contract . That model adapts the failure rate by using the system improvement model of Zhang and Jardine (1998). Such concepts of profitable coordination and imperfect maintenance are also used in the present paper to improve the practical applicability for asset intensive operations.

There are studies that specifically deal with allocation spare parts in service contracts. A paper intending to incorporate repair contract selection and spares provisioning under a multicriteria approach is presented in Teixeira de Almeida (2001). In Nowicki et al. (2008), a profit-centric model is presented for spares provisioning under a logistics contract for multi-item and multi-echelon scenario. In Mirzahosseinian and Piplani (2011), an inventory model is developed for a repairable parts system by varying failure and repair rates. A dynamic stocking policy to replenish the inventory to meet the time-varying spare parts demand is proposed by Jin and Tian (2012). A reliability-based maintenance strategy required for the spares inventory is described in Kurniati and Yeh (2013), although its scope does not cover contract conditions. Since the relevant effect of warranties as service contracting, a three-partite stochastic model including manufacturer, agent, and customer is presented in Gamchi et al. (2013). However, none of these works has faced the pool management problem by using the realistic assumptions of imperfect maintenance, finite contract duration, or profitable channel coordination.

Regardless of the extensive literature, the present paper introduces new contributions in terms of formulation and analytical properties. To the best of our knowledge, a model capable of delivering profitable decisions to allocate the pool of critical spare parts within maintenance outsourcing contracts –via the inclusion of imperfect maintenance and the optimal conditions for supply chain coordination– has not been addressed in the literature.

6.2 Model Formulation

Consider a system belongs to a fleet of equipment whose operation is supported by a pool of repairable components. The proposed model optimizes the management decisions of critical spare components within the outsourcing service contract. The formulation is presented in three sections as follows: (i) preventive maintenance (PM) policy under the contractual conditions scheme, (ii) service level associated with the stock of critical spare parts, and (iii) decision-making model to integrate PM interval with optimal spares inventory to maximize global profits. The terms "client" and "agent" will henceforth be adopted to indicate service receiver and external provider, respectively.

6.2.1 Contractual preventive maintenance policy

Let the maintenance of the fleet system be contracted out by the client to the agent. For sake of self-containment, relevant maintenance contract conditions –such as imperfect maintenance and finite contract horizon– developed in Tarakci et al. (2006a); Pascual et al. (2012); Zhang and Jardine (1998) are described in detail. The scheme is set by the following conditions.

1. The interval between preventive interventions (PM interval) is T.

2. The agent is free to select the age T at which PM will be performed.

3. Direct costs and length of PM are, respectively, C_p and T_p.

4. Direct costs and length of corrective interventions are, respectively, C_r and T_r.

5. The basic service fee to the agent is p.

6. The net revenue of the client after production costs is r.

7. The agent set a minimum expected profit π to participate in the game.

8. The finite horizon is as the contract lasts from the beginning of a system life cycle to the end of the n-th overhaul.

The system has a Weibull distribution with shape parameter

$$\beta > 1. \tag{6.1}$$

The inclusion of imperfect maintenance into the failure rate is based on the system improvement model (Zhang & Jardine, 1998). Each PM intervention restores the system condition according to

$$h_k(t) = \alpha h_{k-1}(t - T) + (1 - \alpha)h_{k-1}(t), \tag{6.2}$$

where t denotes lifetime, k corresponds to the index of the k-th preventive action, and $\alpha \in [0, 1]$ is the maintenance improvement factor.

Table 6-1: Values of κ as inclusion of imperfect maintenance and finite horizon

β	κ
1	n
2	$n^2(1-\alpha)+n\alpha$
3	$n(n-1)(n-2)(1-\alpha)^2+3n(n-1)(1-\alpha)+n$

Before the first preventive intervention, the failure rate is:

$$h(t) = h_0\beta t^{\beta-1}, \quad t < T. \tag{6.3}$$

The expected number of failures H after n overhauls is

$$H(nT) = \sum_{i=0}^{n} \begin{pmatrix} n \\ i \end{pmatrix} \alpha^{n-i}(1-\alpha)^{i-1}H_0(iT), \tag{6.4}$$

where $H_0 = \int_0^{nT} h(t)dt$.

For β integer, the expected number of failures is

$$H(nT) = \kappa h_0 T^{\beta}, \tag{6.5}$$

where values of κ, some of them summarized in Table 6-1, depend on both α and n for different integer values of β. Nevertheless, $H(nT)$ for non-integers values of beta is straightforward to calculate by using generic series defining the expected number of failures for any non-homogeneous Poisson process.

As the duration of the contract is $n\,(T+T_p)$, the expected maintenance direct cost is

$$C_M(nT) = \frac{C_p + H(nT)C_r}{n\,(T+T_p)}. \tag{6.6}$$

In addition, the expected availability during the contract as a function of maintenance interventions is

$$A_M(nT) = \frac{nT - H(nT)T_r}{n\left(T + T_p\right)}. \tag{6.7}$$

From a perspective biased by single interests, it is clear that the client focuses on maximizing availability, whereas the agent focuses on minimizing maintenance costs. To achieve the cooperation of both parties, the next sections describe an optimal PM interval (T) aiming to the entire chain benefit while adding the influence of the critical spares inventory.

6.2.2 Spare components service level

The concept of spare components service level allows incorporating the preventive maintenance policy described in the above-mentioned section. Estimation of system availability as a function of critical spare parts stock is adapted from the inventory model for repairable items developed in Sherbrooke (2004). For sake of conciseness, an one component case is treated but the extension to multi-components is straightforward. The approach is as follows.

- The system belonging to the fleet of equipment requires I types of repairable spare components.

- The fleet size is N and the multiplicity of each type of spare components in the equipment is z_i.

- Stock level of critical spare parts is S.

- Turn-around time, as the workshop repair cycle from removal of a component until readiness to use, is T_{at}.

We propose the following approach to incorporate the impact of PM interval on the critical spare parts demand to workshop. The demand $\lambda(T)$ is updated as a function of each interval T from the maintenance policy by

$$\lambda(T) = \frac{Nz_i}{MTBI(T) + T_p R(T) + T_r\left(1 - R(T)\right)}, \tag{6.8}$$

where $R(T)$ is the reliability function at T and $MTBI(T) = \int_0^T R(t)dt$ is the mean time between interventions.

Expected backorders with spares stock level S, the unfilled number of demands for not having sufficient inventory, is

$$EBO(s) = \sum_{j=S+1}^{\infty} (j - S)\frac{(\lambda(T)T_{at})^j \mathrm{e}^{-(\lambda(T)T_{at})}}{j!}. \tag{6.9}$$

Expected service level of equipment given by spares stock is then

$$A_S(S) = \prod_{i=1}^{I}\left(1 - \frac{EBO_i(S_i)}{Nz_i}\right)^{z_i} \tag{6.10}$$

where the aim is to maximize equipment availability, or analogously to minimize expected backorders, as a function of the optimal investment in critical spare part inventories.

This service level usually corresponds to the fraction of time that equipment can operate because of critical spare parts are at hand. Nevertheless, in this indicator it has been included the maintenance policy from the critical system under contracting. In the next section, both maintenance contracts conditions and spare components service level are linked as an integrated approach.

6.2.3 Optimal integration of maintenance policy with spares service level

The following model provides a decision-making framework to optimally decide whether the spare components pool should be managed by the client or the agent. Taking this premise into account, the system availability of interest is that which integrates the maintenance preventive policy with the spares service level, so that

$$A(nT, S) = 1 - \prod \left(1 - A_M(nT)\right)\left(1 - A_S(S)\right), \tag{6.11}$$

where $A_M(nT)$ is given by Equation (6.7) and $A_S(S)$ by Equation (6.10).

Expected global cost of spares inventory $C_G(S)$ during the contract is

$$C_G(S) = C_v(S) + C_h(S) + C_d(S), \tag{6.12}$$

where

- $C_v(S) = nc_u\left(S_0 + \sum_j S_j\right) \cdot \mathrm{CRF}$ is the discounted acquisition cost of investment in spare parts, where c_u is the new spare acquisition cost, i is the discount factor, and

  $$\mathrm{CRF} = \left(\frac{i(1+i)^{n(T+T_p)}}{i(1+i)^{n(T+T_p)} - 1}\right)$$

  is the capital recovery factor across the contract horizon $n(T + T_p)$.

- $C_h(S) = nc_u\left(S_0 + \sum_j S_j\right) c_{h0} \cdot \mathrm{CRF}$ is the holding cost for keeping inventories at hand, where c_{h0} is the holding cost rate.

- $C_d(S) = c_{d0}(1 - A(nT, S)) \sum_j N_j$ is the downtime cost given by the production loss period, where c_{d0} is the downtime cost rate.

This model is capable of efficiently integrating critical spare parts stockholding with outsourcing contracts design. The main options to handle the spare components pool within the maintenance service contract are presented in the following sections.

6.2.3.1 Option 1: Client manages the pool of spare parts

Option 1 sets the contractual framework in which the client agrees to manage the pool of spare components. In this scenario, although agreement restraints, there are no major incentives for the agent to avoid an indiscriminate use of components. Following the lead of Tarakci et al. (2006a) and Pascual et al. (2012), profits for the supply chain can be adapted as follows.

Let $\Pi_c(nT, S)$ be the expected profit for the client. As the client manages the pool, its profit is affected by the entire spares global cost; that is, acquisition cost, holding cost, and downtime cost. Hence, this profit is

$$\Pi_c(nT, S) = rA(nT, S) - p - C_G(S). \tag{6.13}$$

Moreover, let $\Pi_a(nT, S)$ be the expected profit for the agent. Under this scenario, the profit for the agent is only affected by the service fee and the preventive maintenance cost. That is

$$\Pi_a(nT, S) = p - C_M(nT). \tag{6.14}$$

6.2.3.2 Option 2: Agent manages the pool of spare parts

Option 2 sets the contractual framework in which the agent agrees to handle the pool of spare components. If so, a policy based on rational use of components turns suitable for the agent. Profits for the supply chain are the following.

Although the client does not cover the entire spares global cost, its benefit is still impacted by the related downtime cost. The expected profit for the client is therefore

$$\Pi_c(nT, S) = rA(nT, S) - p - C_d(S). \tag{6.15}$$

As the agent manages the pool, its benefit is affected by both acquisition cost and holding cost. The expected profit for the agent is hereby

$$\Pi_a(nT, S) = p - C_M(nT) - (C_v(S) + C_h(S)). \tag{6.16}$$

Ultimately, the total expected profit for the service chain $\Pi(nT, S)$ valid for both Option 1 and Option 2 is

$$\Pi(nT, S) = rA(nT, S) - C_M(nT) - C_G(S). \tag{6.17}$$

Using this framework, the chain coordination can be achieved by selecting the optimal joint value $[T, S]$ that maximizes $\Pi(nT, S)$. This policy profitably allocates the spare components pool, while both contracting parties obtaining higher benefits than pursuing single objectives separately.

6.2.4 Coordination mechanisms for optimal joint values

Coordination mechanisms can be used to ensure a cooperative setting under the above-mentioned Option 1 and Option 2. Following the lead of Tarakci et al. (2006a) and Pascual et al. (2012), subsidization bonuses on both PM intervals and spares pooling costs can be adapted to set parties joint values $[T, S]$ with the one of the supply chain.

6.2.4.1 Cost subsidization under Option 1

When the PM interval of the agent is higher than optimal T of the supply chain, the client agrees to subsidize the direct cost of PM to create an incentive for the agent. If let ΔC_p be the PM subsidization bonus, the new preventive cost is

$$C_p' = C_p - \Delta C_p. \tag{6.18}$$

The expected profit for the client adding the PM bonus effect is

$$\begin{aligned}\Pi_c(nT, S) &= rA(nT, S) - p - C_G(S) - \frac{n\Delta C_p}{n(T + T_p)} \\ &= rA(nT, S) - p - C_G(S) - \frac{\Delta C_p}{T + T_p}.\end{aligned} \tag{6.19}$$

The expected profit for the agent adding the PM bonus effect is

$$\begin{aligned}\Pi_a(nT, S) &= p - C_M(nT) + \frac{n\Delta C_p}{n(T + T_p)} \\ &= p - C_M(nT) + \frac{\Delta C_p}{T + T_p}.\end{aligned} \tag{6.20}$$

With the optimal selection of ΔC_p, the agent is encouraged to adjust its PM interval as needed for chain coordination.

6.2.4.2 Cost subsidization under Option 2

Since under Option 2 the agent manages the pool, another mechanism is needed to cope with its extra acquisition and holding costs. Although similar to the aforesaid PM bonus, this model is rather based on subsidizing the spares pooling cost. The scheme creates an incentive for selecting the optimal stock level of the chain, while it keeps the benefits of adjusting the PM interval. Let Δc_u be the inventory subsidization bonus, the new acquisition cost is thus

$$c'_u = c_u - \Delta c_u. \tag{6.21}$$

The expected profit for the client adding the pooling bonus effect is

$$\begin{aligned} &\Pi_c(nT, S) = \\ &rA(nT, S) - p - C_d(S) - \frac{\Delta C_p}{T + T_p} - \Delta c_u \left(S_0 + \sum_j S_j \right). \end{aligned} \tag{6.22}$$

The expected profit for the agent adding the pooling bonus effect is

$$\begin{aligned} &\Pi_a(nT, S) = \\ &p - C_M(nT) - (C_v + C_h)(S) + \frac{\Delta C_p}{T + T_p} + \Delta c_u \left(S_0 + \sum_j S_j \right). \end{aligned} \tag{6.23}$$

The cost subsidization models for Option 1 and Option 2 induce the agent to optimally perform both maintenance and stockholding services. Such policy ensures maximum supply chain performance.

6.3 Case study

In the following case study, the critical components of interest are principal alternators of a fleet of haul trucks operating in a copper mining company. This client contracts out the fleet maintenance service to a specialized agent attempting to ensure high equipment performance. The parameters for the preventive maintenance strategy and spare components stockholding are shown in Table 6-2.

Table 6-2: Parameters for the joint maintenance-stockholding model

Management area	Parameter	Value	Unit
Preventive maintenance	h_0	0.001	(1/Kh)
strategy	β	3	
	T_p	1	(Kh)
	T_r	.3	(Kh)
	C_p	8	(KUS$)
	C_r	.4	(KUS$)
	r	1500	(KUS$)
	p	350	(KUS$)
	α	0.95	
	n	5	(overhauls)
Spare components	N	20	(trucks)
stockholding	z_i	1	(alternator/truck)
	T_{at}	933	(h)
	c_u	80	(KUS$)
	c_{d0}	5.3	(KUS$/h/truck)
	c_{h0}	0.1	(1/alternator investment)
	i	0.1	

Figure 6-1 shows the system availability resulting of merging both the availability related to maintenance strategy and the spares stockholding service level. Higher service level can be provided as the spares stock level S increases, but higher investment is required. Moreover, the optimal PM interval T changes over the associated spares stock range. Under the proposed framework, the system availability $A(nT, S)$ is clearly a performance indicator of interest and thereby it is used to coordinate the chain profits during the contract.

Figures 6-2 and 6-3 reveal the differences in profits depending on the allocating position of the critical spare components pool. The results of the aforementioned Option 1 and Option 2 are obtained by solving Equations (6.13) to (6.17) as follows.

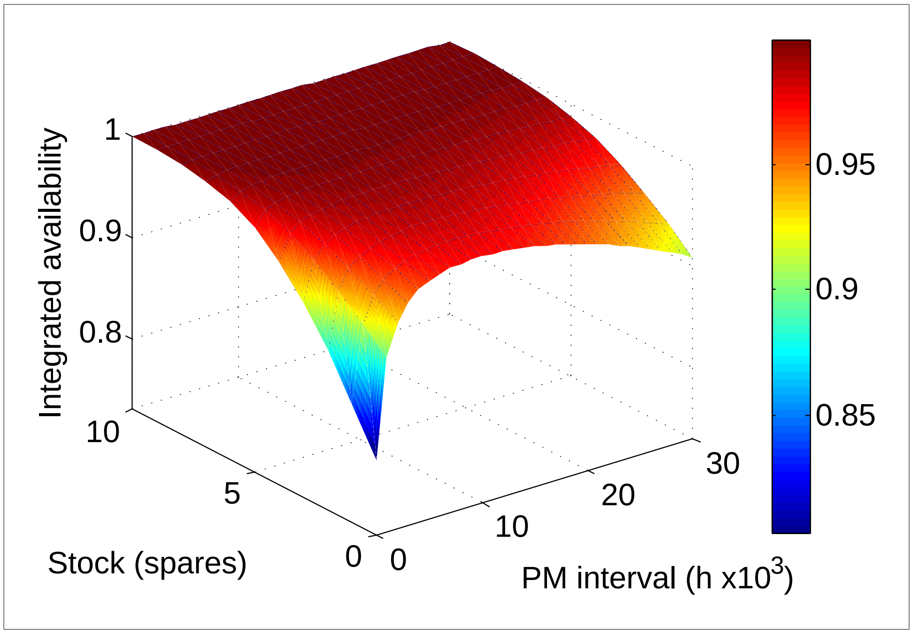

Figure 6-1: System availability by integrating T and S

When the client manages the pool, the joint values $[T, S]$ are $[18 \times 10^3, 0]$ for the agent and $[11 \times 10^3, 3]$ for the client. The corresponding single profits are $\Pi_a(nT, S)$ =US\$ $287,888$ and $\Pi_c(nT, S)$ =US\$ $935,142$. Conversely, when the agent manages the pool, the joint values are $[18 \times 10^3, 0]$ for the agent and $[10 \times 10^3, 10]$ for the client. The respective single profits are $\Pi_a(nT, S)$ =US\$ $287,888$ and $\Pi_c(nT, S)$ =US\$ $1,149,772$. It is considered that p is set to fulfill the profit constraint π. Before subsidization, the corresponding profits for the supply chain by using optimal parties T^* intervals are $\Pi(nT_a^*, S)$ =US\$ $1,169,230$ and $\Pi(nT_c^*, S)$ =US\$ $1,211,243$ for Option 1, and $\Pi(nT_a^*, S)$ =US\$ $1,169,230$ and $\Pi(nT_c^*, S)$ =US\$ $1,206,436$ for Option 2. However, the optimal supply chain joint value $[T^*, S^*]$ is $[15 \times 10^3, 3]$, which leads to a higher profit $\Pi(nT, S)$ =US\$ $1,219,018$. Therefore, the optimal duration of the contract is $n(T^* + T_p) = 5(15 + 1) \times 10^3 = 80 \times 10^3(h)$.

From the previous results, it is clear that taking into account the entire supply chain is the best possible scenario. As anticipated, the agent must be motivated to adjust its PM interval and stock as needed for chain coordination. To achieve this result, the cooperative mechanisms described in Section 6.2.4 are used. Under Option 1, the interval of the agent is certainly higher than desired, thus the client subsidizes the PM cost. In this case, $\Delta C_p = 2.853$ sets the agent's PM interval with the optimal interval of the chain, namely from $T = 18 \times 10^3$ to $T = 15 \times 10^3$. Under Option 2, it is clear that the agent attempts to keep the stock level as low as possible since the extra acquisition and holding costs. Hence, the client decides to subsidize those significant inventory costs. In this case, $\Delta c_u = 55.030$ sets the the stock level with the optimal stock of the chain.

After subsidization, profits for the whole supply chain by using optimal single intervals align with the maximum value $\Pi(nT, S)$ =US\$ $1,219,018$. Nonetheless, as expected, the single profits change across options. For example, the client's profit decreases from US\$$935,142$ (Option 1) and US\$$1,149,772$ (Option 2) to US\$$915,065$ due to to the subsidization mechanism, and the agent's profit increases from US\$$287,888$ to US\$$303,953$. For further details on changes for both subsidization options, Figures 6-4 and 6-5 denote a sensitivity analysis for those optimal joint values that maximize the profit for the entire channel. Note that after the application of both bonuses, the joint values of agent and contractor align with the optimal joint value of the supply chain $[15 \times 10^3, 3]$. Hence, the desired coordination is achieved. As demonstrated, the supply chain benefit is higher than those single profits obtained by the contracting parties. Consequently, the proposed framework motivates both chain parties to improve their maintenance and supply services continuously.

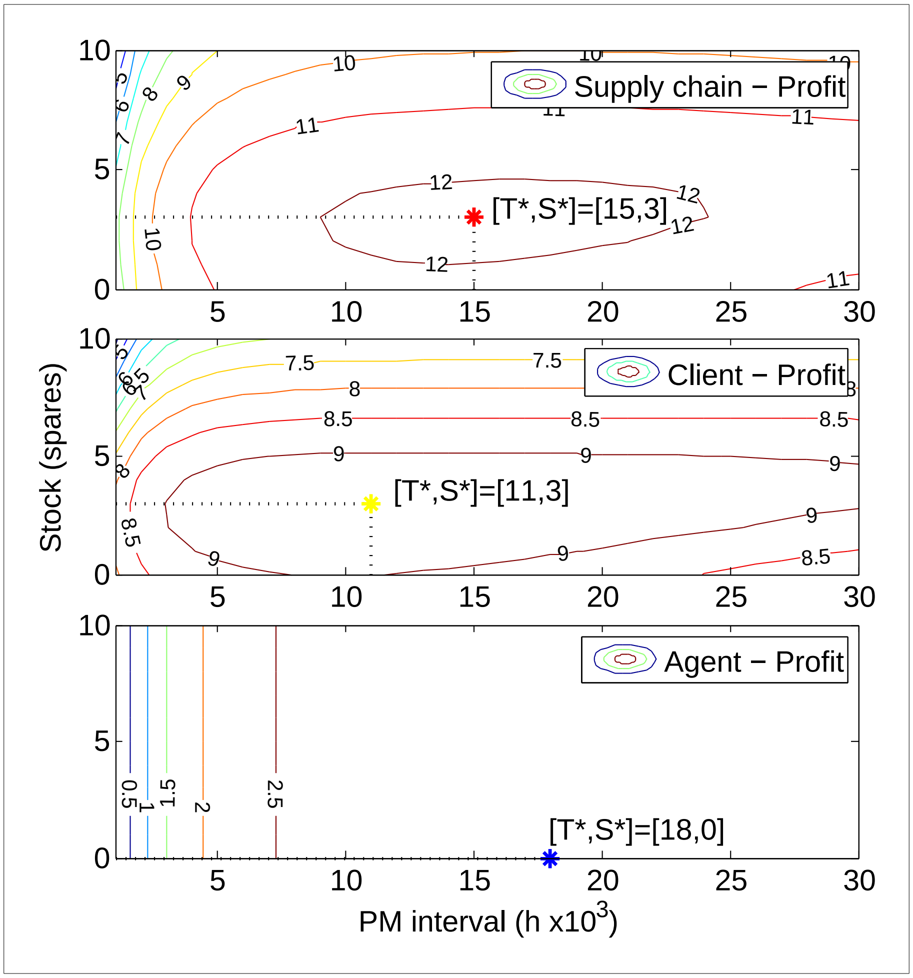

Figure 6-2: Study of optimal T and S when the client manages the pool of spare components

6.4 Conclusions

This chapter has introduced a model for defining the optimal manager of the pool of components within outsourcing services. A decision-making framework has been provided to integrate preventive maintenance with critical spares stockholding for contract profitability. Using an imperfect maintenance strategy over a nite horizon,

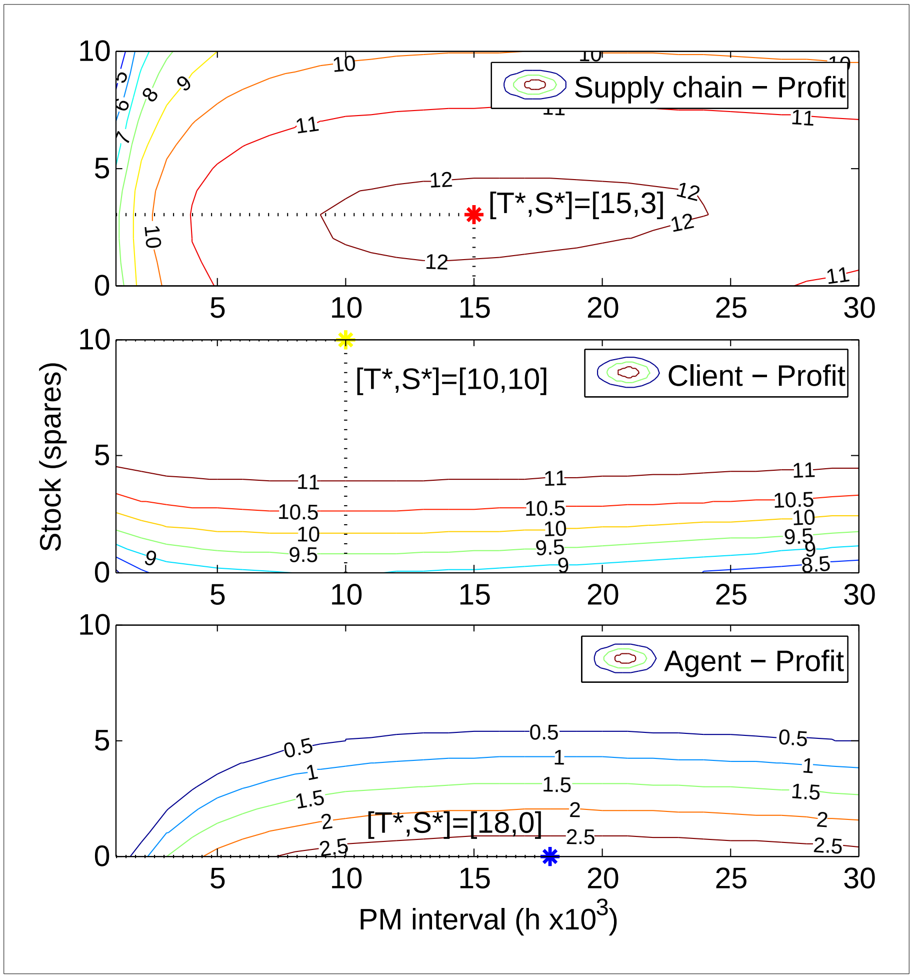

Figure 6-3: Study of optimal T and S when the agent manages the pool of spare components

the allocation scheme induces the parties involved to perform maintenance and supply activities cooperatively, rather than a separated non-optimal way. This aim is achieved by setting an original joint value consisting of the preventive maintenance interval and the spare parts stock level that maximizes the total expected profit for both client and agent.

It has been found the joint values that reach the supply chain coordination for the two options under study, when the client administers the spare components and when the

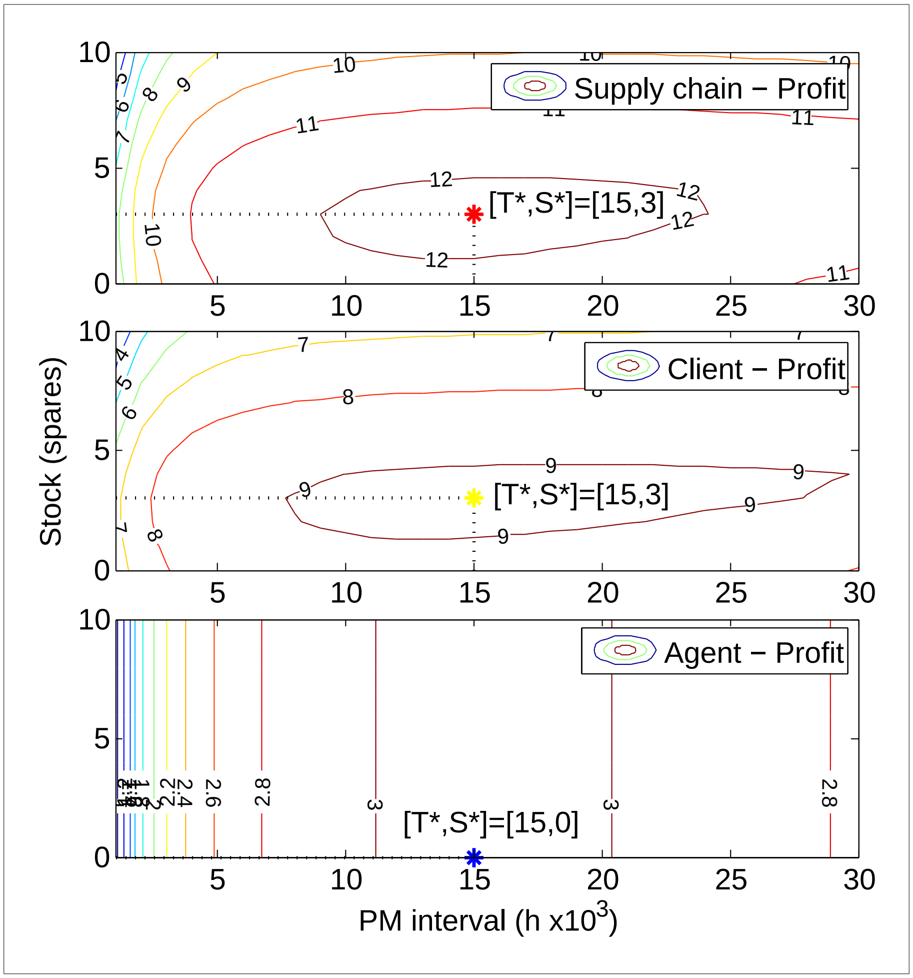

Figure 6-4: Study of optimal T and S when the client subsidizes the PM cost of the agent

agent is the pool manager. However, there are scenarios where the expected profit is not sufficient to drive changes in the policy. To provide an incentive to set parties' joint values with the optimal benefit of the supply chain, subsidization bonuses on both additional PM performed and spares pooling costs are practicable methods. The procedure to estimate such bonuses has been developed.

Finally, we have demonstrated that the model is capable of coordinately optimizing business performance for the entire supply chain. Both client and agent are

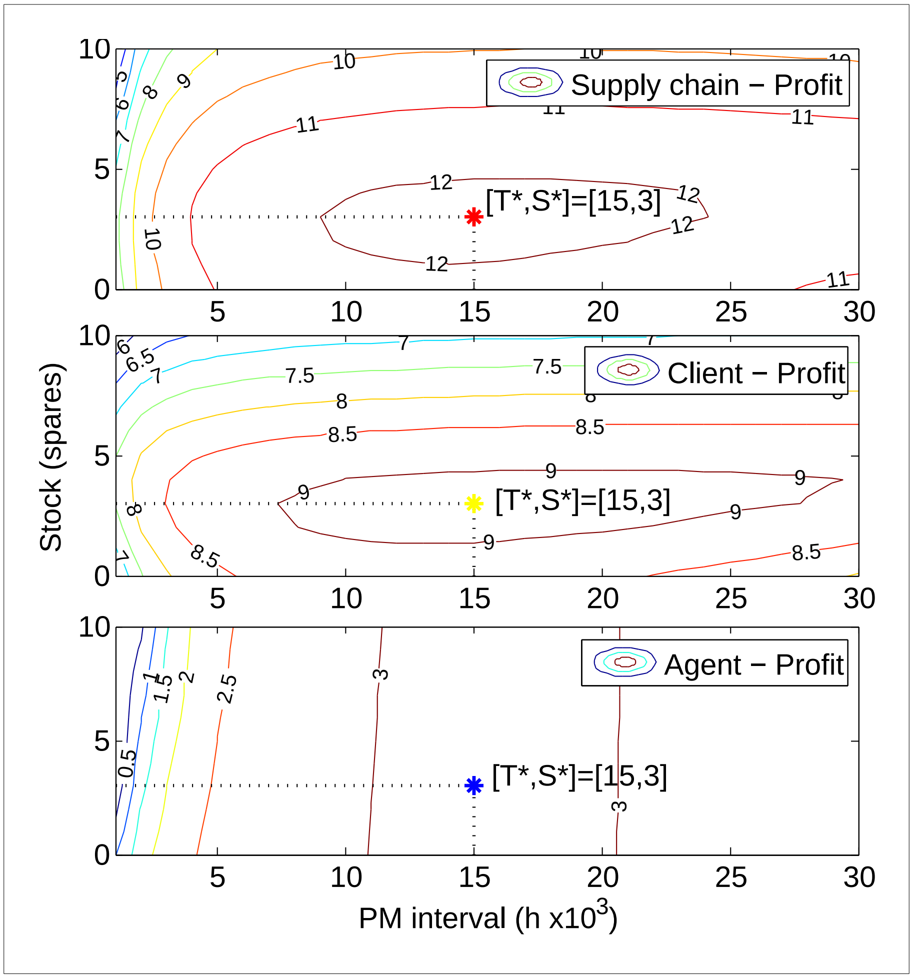

Figure 6-5: Study of optimal T and S when the client subsidizes both acquisition and holding costs of the agent

encouraged to continually improve their maintenance services and supply practices, thus obtaining higher joint benefits compared to those single profits when no coordination occurs. Accordingly, this research has built an interesting bridge between the decision areas of preventive maintenance strategy and spare parts management.

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7. CONCLUSIONS AND AREAS FOR FURTHER RESEARCH

This doctoral thesis has integrated a decision-making framework to optimize the life cycle of critical spare parts under an asset management perspective. This approach has been accomplished by covering every vital stage of the decision process, from selection of the most important resources to supply chain considerations. Interestingly, the research has built a bridge across several asset management goals related to the following areas: throughput requirements, condition-based maintenance, logistics, business value, outsourcing coordination, and joint decisions on reliability engineering and stockholding policies. Several enriched models and user-friendly graphical tools have been developed for the sake of increasing the applicability of both business and quantitative risk analyses by asset managers. In brief, the goal of consolidating an asset management-based decision scheme for critical spares has been addressed in order to efficiently support the enhancement of system performance within equipment intensive industries.

The thesis has been documented by five ISI journal articles that form the integrated decision-making system. As shown by the "List of Papers" chapter, four of them have already been published and the fifth is currently under review by its corresponding journal. Findings, contributions, and areas for further development from these papers –*i.e.* chapters of the thesis– are summarized below.

7.1 Findings

The research objective has been to develop an asset management-based framework to optimize the life cycle of critical spare parts by integrating five key decision areas, namely: prioritization, ordering, replacement, maintenance outsourcing, and pool allocation. As the resulting support system is documented by five ISI journal articles dealing with the key decision areas, this thesis has met the general objective by a sequential addressing of aims and contributions for each appended paper, as follows.

In Chapter 2, a decision-making tool called the *System Efficiency Influence Diagram* (SEID) is provided to prioritize equipment and resources by ranking their impact on system throughput when intermediate buffers –such as stockpiles– are taken into account. This effect on throughput is more interesting to a business perspective than simple machine availability. Since buffers exist, it is highlighted that equipment with greater unavailability factors is not always the most important to prioritize. Even equipment with relatively low investment involved can turn out to be the most critical. When dealing with business as a main focus, equipment with the largest effect in throughput should be ranked as first priority. Therefore, SEID contributes to the evolution to an asset management perspective in place of maintenance policies focusing only on equipment. In this chapter, the asset management perspective is defined by system throughput as a global indicator of interest.

Chapter 3 introduces the concept of *Condition-Based Service Level* (CBSL), which is useful in defining the time at which the system operation is sufficiently reliable to withstand the spares lead time variability. It presents a graphical technique based on both conditional reliability and stochastic or fixed lead time. Such a technique allows the spares ordering decision to be enhanced to satisfy the desired CBSL. The ordering policy turns out to be sensitive to both conditional reliability variables and lead time scenarios, modifying decisions for similar service level thresholds.

Chapter 4 shows the influence of business value on the optimal epoch for major component replacements when facing lengthy shutdowns. This work continually monitors the performance of high financial impact interventions, while satisfying both reliability and time window constraints.

In Chapter 5, a systemic rewarding win-win coordination is set by proposed contract conditions that encourage service receivers (clients) and external providers (agents) to continuously improve their maintenance services. A preventive maintenance strategy maximizes the supply chain's expected profit. Previous research is extended by considering imperfect maintenance and the realistic finite horizon of contracts. Profit and non-profit-centered customers are included. Results show that the contracting parties involved can achieve a higher benefit than any obtained separately.

In Chapter 6, a model is elaborated to profitably allocate the pool of spare components within the maintenance service contract. A new joint value –consisting of the preventive maintenance interval and spare parts stock level– maximizes the total expected profit for both client and agent. Two management options are considered: when the client is the manager of the group of spares, and when the agent handles the components pool. When the expected profit is insufficient to drive changes in policies, the procedure for estimating subsidizing bonuses and break-even fees is introduced.

7.2 Original Contributions

This thesis provides asset managers with integrated decision-making models to optimize the life cycle of critical spares under an asset management perspective. The research builds an interesting bridge across the areas of condition-based maintenance, outsourcing coordination, and joint decisions on reliability engineering and stockholding policies. The original contributions of this thesis are outlined as follows.

- The graphical prioritization tool provided, SEID, is capable of effectively quantifying the impact of equipment on system throughput. It avoids prioritizing on an equipment level and setting priorities only with capital investments as criteria. This technique can be useful for making decisions about maintenance policies and redesigning buffer capacities.

- To address the need for effective decision-making, the graphical tool for ordering spares based on the CBSL decision rule helps to ensure operational continuity of the equipment supported by the spare parts stock.

- The value-adding decision rule, applied in components replacement, has enriched the decision-making process by quantifying the real value of postponing or accelerating the most favorable epoch to perform an intervention.

- In maintenance outsourcing, the asset management strategy is illustrated by the contractual conditions to pursue the entire system profit instead of single benefits. In this coordinated scenario, the contracting parties jointly optimize their actions, thus improving overall financial and maintenance policies.

- The asset management perspective of pooling allocation is denoted by the interesting joint model that integrates reliability engineering and spares stockholding policies for global contract profitability. The original joint value provided –consisting of the preventive maintenance interval and the spare parts stock level– allows the maximization of total expected profit for both the service receiver and external provider.

In summary, the methodology and integrated models presented in this thesis contribute to continuous improvement and firm profitability since business-oriented approaches are included. The enriched models and graphical tools developed in these chapters –i.e. papers– are useful for operations design and major planning within critical spare parts management.

7.3 Recommendations for Future Research

The areas for future research are organized as the papers were introduced in the thesis. These recommendations are indicated as follows.

- Future works in prioritization could incorporate the issue of redesigning the buffers within the SEID technique. In this case, it is also possible to create a scatter diagram with one axis for the efficiency influence factor, one for the unavailability factor, and one for normalized buffer capacity. Another possible extension is to unbalance the operating lines in pursuit of increasing the expected productivity rate.

- The asset management approach pursued by this thesis is characterized in spares ordering by the inclusion of logistics considerations into the reliability engineering analysis. Merging CBSL with associated maintenance and logistics costs is an opportunity for model enhancement in order to enrich the desired global perspective.

- In the case of value-adding intervention intervals, although copper prices were included in the analysis, the use of other performance measurements is a reasonable option to include in future work.

- For maintenance outsourcing, a direct extension of the formulation presented in this thesis is to consider how the replacement may affect the conditions of the service contract.

- As an area for further research into spares pool allocation, the model can be extended to include the maximization of the service chain discounted profit over a finite or infinite time horizon. It is also interesting to explore further modeling of the coordination problem under the approach of Supply Chain and Management Science (rather than Reliability Engineering). This last issue is also an indicator that there is a potential significant impact from the solid quantitative view and sophisticated modeling that have been presented in this thesis.

This thesis provides asset managers wishing to optimize the entire life cycle of spare parts with five key decision areas, which are critical to performance excellence and hence to business success of equipment intensive industries. The resulting integrated decision-making models contribute to the continuous improvement and firm profitability, since the problem areas covered include value-adding approaches within an asset management conception. The criticality of the spare components considered merits the use of complex models and graphical tools, which supply useful decision elements in long-term plant design processes and major planning. In summary, every section of this research is dedicated to ensuring an optimal way of managing critical spares to attain a sustainable organization outcome. The thesis has confirmed the value of evolving from a maintenance vision, biased by local subsystems, to a systemic viewpoint of the whole business: the physical asset management perspective.

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APPENDIX

A. PROOF OF LEMMAS

PROOF OF LEMMA 5.1. Without the loss of generality, we prove the condition of optimality for the client (Equation 5.11). To find the PM interval that maximizes $\Pi_m(nT)$, we have to consider its first and second derivative with respect to T. It is easy to show that:

$$\frac{\partial \Pi_m(nT)}{\partial T} = R\frac{n^2T_p - \kappa\lambda_0 nT_r\left((\beta-1)T^\beta + \beta T_pT^{\beta-1}\right)}{\left(n(T+T_p)\right)^2} \tag{A.1}$$

According to the first order optimality condition, setting $\frac{\partial \Pi_m(nT)}{\partial T} = 0$, we obtain the following Equation for T, in order to search critical points of $\Pi_m(nT)$:

$$n^2T_p - \kappa\lambda_0 nT_r\left((\beta-1)T^\beta + \beta T_pT^{\beta-1}\right) = 0 \tag{A.2}$$

Or equivalently:

$$n^2T_p - nT_rg_\alpha(T) = 0 \tag{A.3}$$

The PM T that satisfies Equation A.3 is called T_m^*. T_m^* exists because $g_\alpha(0) = 0$, $g_\alpha(T)$ is a continuous function, increasing and unbounded. Finally, from Equation A.3 we can conclude that:

$$g_\alpha(T_m^*) = n\frac{T_p}{T_r} \tag{A.4}$$

The second derivative of $\Pi_m(nT)$ with respect to T is given for:

$$\begin{aligned}\frac{\partial^2 \Pi_m(nT)}{\partial T^2} &= -R\frac{n\lambda_0\kappa T_r(\beta-1)(\beta-2)T^\beta + 2n\lambda_0\kappa T_r\beta(\beta-2)T_pT^{\beta-1}}{n^2(T+T_p)^3} \\ &- R\frac{n\lambda_0\kappa T_r\beta(\beta-1)T_p^2T^{\beta-2} + 2n^2T_p}{n^2(T+T_p)^3}\end{aligned} \tag{A.5}$$

If $\beta \geq 2$, $\frac{\partial^2 \Pi_m(nT)}{\partial T^2}$ is negative for all $T > 0$ and, then, $\Pi_m(nT)$ is a strictly concave function of T and, as T_m^* satisfies the first order optimality condition, we can conclude that T_m^* is the global maximum of the $\Pi_m(nT)$ function. Moreover, this fact proves that T_m^* is unique. In an analogous way, we can prove parts (2) and (3) of the Lemma. $\square$

PROOF OF LEMMA 5.2. 1. Given $\lambda_0^1, \lambda_0^2, c \in c^+$, $\lambda_0^2 > \lambda_0^1$. Suppose that:

$$\kappa\lambda_0^1\left(\left(\beta-1\right)T_1^{\beta}+\beta T_p T_1^{\beta-1}\right)=c \tag{A.6}$$

$$\kappa\lambda_0^2\left(\left(\beta-1\right)T_2^{\beta}+\beta T_p T_2^{\beta-1}\right)=c \tag{A.7}$$

Then,

$$\frac{\left(\beta-1\right)T_1^{\beta}+\beta T_p T_1^{\beta-1}}{\left(\beta-1\right)T_2^{\beta}+\beta T_p T_2^{\beta-1}}=\frac{\lambda_0^2}{\lambda_0^1}>1 \tag{A.8}$$

Thus,

$$\left(\beta-1\right)T_1^{\beta}+\beta T_p T_1^{\beta-1}>\left(\beta-1\right)T_2^{\beta}+\beta T_p T_2^{\beta-1} \tag{A.9}$$

Is easy to see, for $\beta > 1$, that function f define as $f(T) = (\beta-1)\,T^{\beta}+\beta T_p T^{\beta-1}$, $T \in R^+$, is an increasing function in T. Therefore, from Equation A.9 we conclude that $T_1 > T_2$. As c is any positive real, in particular, we can take either $c = \frac{nT_p}{T_r}$, $c = \frac{nC_p}{C_r}$ or $c = n\frac{RT_p+C_p}{RT_r+C_r}$, and conclude that, for each case, if the scale parameter increases, then the optimal preventive interval will decrease. In an analogous way, we can prove that if the shape parameter increases, then the optimal preventive interval will decrease too.

2. Considerer two preventive maintenance times, T_{p_1} and T_{p_2}, $T_{p_2} > T_{p_1}$, and the following two optimality conditions for the client:

$$\kappa\lambda_0\left(\left(\beta-1\right)T_1^{\beta}+\beta T_{p_1} T_1^{\beta-1}\right)=\frac{nT_{p_1}}{T_r} \tag{A.10}$$

$$\kappa\lambda_0\left(\left(\beta-1\right)T_2^{\beta}+\beta T_{p_2}T_2^{\beta-1}\right)=\frac{nT_{p_2}}{T_r} \tag{A.11}$$

Or equivalently,

$$c_1=\frac{\kappa\lambda_0\left(\beta-1\right)T_1^{\beta}}{T_{p_1}}+\beta T_1^{\beta-1}=\frac{n}{T_r} \tag{A.12}$$

$$c_2=\frac{\kappa\lambda_0\left(\beta-1\right)T_2^{\beta}}{T_{p_2}}+\beta T_2^{\beta-1}=\frac{n}{T_r} \tag{A.13}$$

As $T_{p_2}>T_{p_1}$, then $\frac{1}{T_{p_1}}>\frac{1}{T_{p_2}}$. Now, suppose that $T_1>T_2$, thus:

$$c_1=\frac{\kappa\lambda_0\left(\beta-1\right)T_1^{\beta}}{T_{p_1}}+\beta T_1^{\beta-1}>\frac{\kappa\lambda_0\left(\beta-1\right)T_2^{\beta}}{T_{p_2}}+\beta T_2^{\beta-1}=c_2 \tag{A.14}$$

The statement in Equation A.14 is a contradiction, because for definition $c_1=c_2$, therefore $T_1<T_2$. This fact means that the optimal preventive interval for the client increases in the preventive maintenance time. On the other hand, considerer the optimal condition for the contractor given for the following Equation:

$$\kappa\lambda_0\left(\left(\beta-1\right)T^{\beta}+\beta T_pT^{\beta-1}\right)=\frac{nC_p}{C_r} \tag{A.15}$$

$$\left(\left(\beta-1\right)T^{\beta}+\beta T_pT^{\beta-1}\right)=\frac{nC_p}{C_r\kappa\lambda_0} \tag{A.16}$$

In *ceteris paribus* condition, the right hand of Equation A.16 holds constant, thus, if we increase T_p, T must be lower in order to balance the equation, in other words, the optimal PM interval for the contractor decreases if preventive maintenance time increases.

$\square$

PROOF OF LEMMA 5.3. For induction: For n=1, the truthfulness of the statement is shown. Suppose that Equation 5.15 is true for certain n. Now, we have to prove that:

$$\kappa(\alpha, n+1) \geq n+1 \tag{A.17}$$

Equation A.17 is equivalent to:

$$\kappa(\alpha, n+1) = \sum_{i=0}^{n+1} \binom{n+1}{i} \alpha^{n+1-i}(1-\alpha)^{i-1} i^{\beta} \geq n+1 \tag{A.18}$$

If we concentrate on the left hand of Equation A.18, thanks to Pascal's identity we can state that:

$$\sum_{i=0}^{n+1} \binom{n+1}{i} \alpha^{n+1-i}(1-\alpha)^{i-1} i^{\beta} = \sum_{i=0}^{n+1} \left(\binom{n}{i-1} + \binom{n}{i} \right) \alpha^{n+1-i}(1-\alpha)^{i-1} i^{\beta} \tag{A.19}$$

Thus,

$$\begin{aligned} \kappa(\alpha, n+1) = & \sum_{i=0}^{n} \binom{n}{i-1} \alpha^{n+1-i}(1-\alpha)^{i-1} i^{\beta} + \\ & \sum_{i=0}^{n} \binom{n}{i} \alpha^{n+1-i}(1-\alpha)^{i-1} i^{\beta} + (1-\alpha)^{n}(n+1)^{\beta} \end{aligned} \tag{A.20}$$

Now, the first term on the right hand can be developed as follows:

$$\sum_{i=0}^{n} \binom{n}{i-1} \alpha^{n+1-i}(1-\alpha)^{i-1} i^{\beta} = \sum_{i=1}^{n} \binom{n}{i-1} \alpha^{n+1-i}(1-\alpha)^{i-1} i^{\beta} \tag{A.21}$$

$$= \sum_{i=0}^{n-1} \binom{n}{i} \alpha^{n-i}(1-\alpha)^{i}(i+1)^{\beta} \tag{A.22}$$

For $\beta \geq 1$, $(i+1)^{\beta} \geq i^{\beta} + 1$, $\forall n \in N$. So,

$$\sum_{i=0}^{n-1} \binom{n}{i} \alpha^{n-i}(1-\alpha)^{i}(i+1)^{\beta} \geq \sum_{i=0}^{n-1} \binom{n}{i} \alpha^{n-i}(1-\alpha)^{i} i^{\beta} + \sum_{i=0}^{n-1} \binom{n}{i} \alpha^{n-i}(1-\alpha)^{i} = \tau_1 \tag{A.23}$$

But,

$$\tau_1 = (1-\alpha)\left(\sum_{i=0}^{n}\binom{n}{i}\alpha^{n-i}(1-\alpha)^{i-1}i^{\beta} - (1-\alpha)^{n-1}n^{\beta}\right) + (\alpha+1-\alpha)^n - (1-\alpha)^n \tag{A.24}$$

By inductive hypothesis, $\sum_{i=0}^{n}\binom{n}{i}\alpha^{n-i}(1-\alpha)^{i-1}i^{\beta} \geq n$, Hence:

$$\tau_1 \geq (1-\alpha)\left(n - (1-\alpha)^{n-1}n^{\beta}\right) + 1 - (1-\alpha)^n \tag{A.25}$$

On the other hand; the second term in Equation A.18 can be bounded in the following way:

$$\sum_{i=0}^{n}\binom{n}{i}\alpha^{n+1-i}(1-\alpha)^{i-1}i^{\beta} = \alpha\sum_{i=0}^{n}\binom{n}{i}\alpha^{n+1-i}(1-\alpha)^{i-1}i^{\beta} \geq \alpha n \tag{A.26}$$

Finally, applying the inequality A.25 and Equation A.26 in Equation A.18, we can state that:

$$\begin{aligned}\sum_{i=0}^{n+1}\binom{n+1}{i}\alpha^{n+1-i}(1-\alpha)^{i-1}i^{\beta} \geq & (1-\alpha)\left(n - (1-\alpha)^{n-1}n^{\beta}\right) + \\ & 1 - (1-\alpha)^n + \alpha n + (1-\alpha)^n(n+1)^{\beta}\end{aligned} \tag{A.27}$$

Simplifying;

$$\sum_{i=0}^{n+1}\binom{n+1}{i}\alpha^{n+1-i}(1-\alpha)^{i-1}i^{\beta} \geq n + 1 + (1-\alpha)^n((n+1)^{\beta} - n^{\beta} - 1) \tag{A.28}$$

As $(1-\alpha)^n((n+1)^{\beta} - n^{\beta} - 1) \geq 0$ for $\beta \geq 1$, $\alpha \in [0,1]$ and $n \in N$, then

$$\sum_{i=0}^{n+1}\binom{n+1}{i}\alpha^{n+1-i}(1-\alpha)^{i-1}i^{\beta} \geq n + 1 \tag{A.29}$$

□

PROOF OF LEMMA 5.4.

$$\left(n\binom{n+1}{i} - (n+1)\binom{n}{i}\right) i^\beta = \left(\frac{n(n+1)!}{(n+1-i)!i!} - \frac{(n+1)!}{(n-i)!i!}\right) i^\beta \quad (A.30)$$

$$= \frac{(n+1)!}{(n-i)!i!}\left(\frac{n}{n+1-i} - 1\right) i^\beta \quad (A.31)$$

$$= \frac{(n+1)!}{(n+1-i)!i!}(i-1)i^\beta \quad (A.32)$$

But, as $\beta \geq 1$ and $i \in N$, then $i^\beta \geq (i-1)^\beta$. Therefore, from Equation A.32 we can conclude:

$$\frac{(n+1)!}{(n+1-i)!i!}(i-1)i^\beta \geq \frac{(n+1)!}{(n+1-i)!i!}(i-1)(i-1)^\beta \quad (A.33)$$

$$= \frac{(n+1)!}{(n+1-i)!(i-1)!}(i-1)^\beta \quad (A.34)$$

$$= (n+1)\binom{n}{i-1}(i-1)^\beta \quad (A.35)$$

□

PROOF OF LEMMA 5.5. Prove Equation 5.17 is equivalent to show that:

$$n\kappa(\alpha, n+1) - (n+1)\kappa(\alpha, n) \geq 0 \quad (A.36)$$

And we choose this alternative for proving the statement. Using the definition of $\kappa(\alpha, n)$ we can state:

$$n\kappa(\alpha, n+1) - (n+1)\kappa(\alpha, n) = n\sum_{i=0}^{n+1}\binom{n+1}{i}\alpha^{n-i}(1-\alpha)^{i-1}i^\beta$$

$$- (n+1)\sum_{i=0}^{n}\binom{n}{i}\alpha^{n-i}(1-\alpha)^{i-1}i^\beta \quad (A.37)$$

$$= \theta_1 \quad (A.38)$$

Developing θ_1;

$$\theta_1 = \sum_{i=0}^{n+1} n\binom{n+1}{i}\alpha^{n-i}(1-\alpha)^{i-1}i^{\beta} - \sum_{i=0}^{n}(n+1)\binom{n}{i}\alpha^{n-i}(1-\alpha)^{i-1}i^{\beta} \tag{A.39}$$

We can re-write the last Equation in a more convenient way:

$$\begin{aligned}
\theta_1 &= n(1-\alpha)^n(n+1)^{\beta} + \sum_{i=0}^{n}\left(n\binom{n+1}{i} - (n+1)\binom{n}{i}\right)\alpha^{n+1-i}(1-\alpha)^{i-1}i^{\beta} \\
&+ \sum_{i=0}^{n}(n+1)\binom{n}{i}\alpha^{n+1-i}(1-\alpha)^{i-1}i^{\beta} - \sum_{i=0}^{n}(n+1)\binom{n}{i}\alpha^{n-i}(1-\alpha)^{i-1}i^{\beta} \\
&= n(1-\alpha)^n(n+1)^{\beta} + \sum_{i=0}^{n}\left(n\binom{n+1}{i} - (n+1)\binom{n}{i}\right)\alpha^{n+1-i}(1-\alpha)^{i-1}i^{\beta} \\
&+ \sum_{i=0}^{n}(n+1)\binom{n}{i}\alpha^{n-i}(1-\alpha)^{i-1}i^{\beta}(\alpha-1) \\
&= n(1-\alpha)^n(n+1)^{\beta} + \sum_{i=0}^{n}\left(n\binom{n+1}{i} - (n+1)\binom{n}{i}\right)\alpha^{n+1-i}(1-\alpha)^{i-1}i^{\beta} \\
&- \sum_{i=1}^{n+1}(n+1)\binom{n}{i-1}\alpha^{n+1-i}(1-\alpha)^{i-1}(i-1)^{\beta}
\end{aligned} \tag{A.40}$$

Notice that the term for $i = 0$ in the first sum in Equation A.40 is null, so we can state that:

$$\begin{aligned}
\theta_1 &= n(1-\alpha)^n(n+1)^{\beta} + \sum_{i=1}^{n}\left(n\binom{n+1}{i} - (n+1)\binom{n}{i}\right)\alpha^{n+1-i}(1-\alpha)^{i-1}i^{\beta} \\
&- \sum_{i=1}^{n+1}(n+1)\binom{n}{i-1}\alpha^{n+1-i}(1-\alpha)^{i-1}(i-1)^{\beta} \\
&= \sum_{i=1}^{n}\left(\left[n\binom{n+1}{i} - (n+1)\binom{n}{i}\right]i^{\beta} - (n+1)\binom{n}{i-1}(i-1)^{\beta}\right)\alpha^{n+1-i}(1-\alpha)^{i-1} \\
&+ (1-\alpha)^n\left(n(n+1)^{\beta} - (n+1)n^{\beta}\right)
\end{aligned} \tag{A.41}$$

Thanks to Lemma 5.4 we know that, for all $0 \leq i \leq n$:

$$\left(\left[n\binom{n+1}{i} - (n+1)\binom{n}{i}\right]i^{\beta} - (n+1)\binom{n}{i-1}(i-1)^{\beta}\right) \geq 0 \tag{A.42}$$

Moreover, $\alpha \geq 0$, $(1-\alpha) \geq 0$ and $n(n+1)^{\beta} - (n+1)n^{\beta} \geq 0$, if $\beta \geq 1$ and $n \in N$, considering this we can conclude that every term in Equation A.41 is positive, then $\theta_1 \geq 0$.

$\square$

B. FULL VERSIONS OF ISI JOURNAL ARTICLES AS LEADING AUTHOR

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A decision-making framework to integrate maintenance contract conditions with critical spares management

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ABSTRACT

Maintenance outsourcing is a strategic driver for asset intensive industries pursuing to enhance supply chain performance. Spare parts management plays a relevant role in this premise since its significant impact on equipment availability, and hence on business success. Designing critical spares policies might therefore seriously affect maintenance contracts profitability, yet service receivers and external providers traditionally attempt to benefit separately. To coordinate both chain parties, we investigated whether the spare components pool should be managed in-house or contracted out. This paper provides a decision-making framework to efficiently integrate contractual conditions with critical spares stockholding. Using an imperfect maintenance strategy over a finite horizon, the scheme maximizes chain returns whilst evaluating the impact of an additional part to stock. As result, an original joint value – preventive interval and stock level – sets the optimal agreement to profitably allocate the components pool within the service contract. Subsidization bonuses on preventive interventions and pooling costs are also estimated to induce the service provider to adjust its policy when needed. The proposed contractual conditions motivate stakeholders to continuously improve maintenance performance and supply practices, thus obtaining higher joint benefits.

1. Introduction

Maintenance outsourcing is a strategic means to improve business performance. Outsourcing creates value through the use of external resources by and for companies to acquire and sustain competitiveness [1]. The maintenance function is a main driver of outsourcing since it has excellent potential to achieve cost benefits and enhance performance among partners [2]. This business purpose is meaningful for asset intensive industries – such as mining, aeronautic, or defence – which face substantial investment in maintaining complex equipment and high demand on system availability. For these firms, the main reasons to contract out maintenance tasks rather than perform them in-house are focusing on core business, accessing highly specialized services at competitive costs, and sharing risks [2–5]. When dealing with outsourcing, effective supply chain coordination allows achieving a rewarding situation for all stakeholders [3]. Accordingly, a model capable of coordinately optimizing performance can lead to successful maintenance contracting strategies in capital intensive environments.

Spare parts management has a critical role toward operational efficiency of asset intensive industries. Equipment criticality is defined by the most relevant assets that efficiently and safely sustain production [6]. The operation of such equipment is consequently supported by critical spare parts [7]. Major spare components are related to considerable investment, high reliability requirements, extended lead times, and plant shutdowns with important effects on operational continuity [8]. A method to prevent production loss events is having inventories at hand, especially when either target service levels or backorder penalties are large [9]. This is the case of capital intensive firms, wherein critical spares storage is directly linked to business success due to the impact of stock-outs on assets utilization [7]. As an example, the aviation supply chain holds a remarkable US$ 50 billion in spares inventories to provide availability service [10]. Efficient critical spares stockholding is therefore essential for companies in which success strongly depends on equipment performance.

Maintenance contracts profitability can be significantly affected by critical spares policies. Particularly, the stock of critical repairable spares can be interpreted as a pool of components from where replacements are satisfied [7]. Consistently with the serious impact on operational and financial performance, managing the pool of critical spare components becomes a key to improve profits within the service contract. Nevertheless, as it depends

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Figure B.1: **Paper V**. Corresponding author: David R. Godoy Ramos on the decision-maker's position, both supply chain parties – service receiver (client) and external provider (agent) – traditionally intend to maximize benefits separately. If the client controls the spare parts pool, there are scarce incentives for the provider to avoid an indiscriminate use of components aside from regular restraints. Conversely, if the agent administers the pool, rational use of components turns reasonable. Critical spares stockholding is a supply chain lever to keep maintenance outsourcing viable for the parties involved.

In order to coordinate the contracting parties, we investigated whether or not the client should outsource the management of the pool of spare components to the agent. This paper provides a decision-making framework to profitably integrate the contractual maintenance strategy with critical spares stockholding. The scheme is based on a joint value – preventive interval and stock level – that maximizes the supply chain returns whilst evaluating the impact of an additional part to stock. Using an imperfect maintenance strategy over a finite horizon, the model leads to an optimal decision to allocate the critical spare components pool within the outsourcing contract. An interesting link is thus created between maintenance performance indicators and supply chain practices.

Having introduced the importance of allocating critical spare parts management within maintenance service contracts for asset intensive industries, the rest of the paper is organized as follows. Section 2 states the differences between the enriched concept of the present paper and relevant existent researches. Section 3 describes the model formulation to integrate maintenance and spares supply indicators. Section 4 presents a case study in the mining industry, which holds substantial spares inventories to ensure system performance. Finally, Section 5 provides the main implications of applying the joint model to coordinate the outsourcing strategy under an asset management perspective.

2. Literature review

The following literature review is structured as the importance of the management of the pool of critical spares within maintenance outsourcing contracts.

As an interesting strategy to achieve cost-benefits, consolidating inventory locations by cooperative pooling has been addressed in [10–13], among other studies. In the context of repairable spares pooling, the cost allocation problem is analyzed using game theoretic models in [14]. Recent implementations are a virtual pooled inventory by managing information systems [15] and a calculation model of spare parts demand, storage and purchase planning in the coal mining industry [16]. When dealing with cooperation in contractual alliances, the study of [17] states the relevance of interfirm trust to deter opportunistic behaviour in a shared ownership structure. Such trust is an important issue related to pooling strategies. A widely applied modeling for repairable items stockholding focused on system availability and spares investment is provided in [18]. Since its accuracy to determine the optimal inventory levels for both single-site and multi-echelon techniques, the above-mentioned model is used to adapt the concept of spare service level in the present paper.

Maintenance outsourcing under supply chain coordination is discussed in [3], a study that deals with incentive contracts terms to coordinate agents and clients by a maintenance policy seeking to optimize the total profit. The work of [4] extends this approach by incorporating realistic conditions, such as imperfect maintenance and finite time-span contract. That model adapts the failure rate by using the system improvement model of [19]. Such concepts of profitable coordination and imperfect maintenance are also used in the present paper to improve the practical applicability for asset intensive operations.

There are studies that specifically deal with allocation spare parts in service contracts. A paper intending to incorporate repair contract selection and spares provisioning under a multicriteria approach is presented in [20]. In [21], a profit-centric model is presented for spares provisioning under a logistics contract for multi-item and multi-echelon scenario. In [22], an inventory model is developed for a repairable parts system by varying failure and repair rates. A dynamic stocking policy to replenish the inventory to meet the time-varying spare parts demand is proposed in [23]. A reliability-based maintenance strategy required for the spares inventory is described in [24], although its scope does not cover contract conditions. Since the relevant effect of warranties as service contracting, a three-partite stochastic model including manufacturer, agent, and customer is presented in [25]. However, none of these works has faced the pool management problem by using the realistic assumptions of imperfect maintenance, finite contract duration, or profitable channel coordination.

Regardless of the extensive literature, the present paper introduces new contributions in terms of formulation and analytical properties. To the best of our knowledge, a model capable of delivering profitable decisions to allocate the pool of critical spare parts within maintenance outsourcing contracts – via the inclusion of imperfect maintenance and the optimal conditions for supply chain coordination – has not been addressed in the literature.

3. Model formulation

Consider a system belongs to a fleet of equipment whose operation is supported by a pool of repairable components. The proposed model optimizes the management decisions of critical spare components within the outsourcing service contract. The formulation is presented in three sections as follows: (i) preventive maintenance (PM) policy under the contractual conditions scheme, (ii) service level associated with the stock of critical spare parts, and (iii) decision-making model to integrate PM interval with optimal spares inventory to maximize global profits. The terms "client" and "agent" will henceforth be adopted to indicate service receiver and external provider, respectively.

3.1. Contractual preventive maintenance policy

Let the maintenance of the fleet system be contracted out by the client to the agent. For sake of self-containment, relevant maintenance contract conditions – such as imperfect maintenance and finite contract horizon – developed in [3,4,19] are described in detail. The scheme is set by the following conditions.

- The interval between preventive interventions (PM interval) is T.
- The agent is free to select the age T at which PM will be performed.
- Direct costs and length of PM are, respectively, C_p and T_p.
- Direct costs and length of corrective interventions are, respectively, C_r and T_r.
- The basic service fee to the agent is p.
- The net revenue of the client after production costs is r.
- The agent sets a minimum expected profit π to participate in the game.
- The finite horizon is as the contract lasts from the beginning of a system life cycle to the end of the n-th overhaul.

The system has a Weibull distribution with shape parameter

$$\beta > 1. \tag{1}$$

The inclusion of imperfect maintenance into the failure rate is based on the system improvement model [19]. Each PM intervention restores the system condition according to

$$h_k(t) = \alpha h_{k-1}(t-T) + (1-\alpha) h_{k-1}(t) \quad (2)$$

where t denotes lifetime, k corresponds to the index of the k-th preventive action, and $\alpha \in [0,1]$ is the maintenance improvement factor.

Before the first preventive intervention, the failure rate is

$$h(t) = h_0 \beta t^{\beta-1}, \quad t < T. \quad (3)$$

The expected number of failures H after n overhauls is

$$H(nT) = \sum_{i=0}^{n} \binom{n}{i} \alpha^{n-i} (1-\alpha)^{i-1} H_0(iT) \quad (4)$$

where $H_0 = \int_0^{nT} h(t)\, dt$.

For β integer, the expected number of failures is

$$H(nT) = \kappa h_0 T^{\beta} \quad (5)$$

where values of κ, some of them summarized in Table 1, depend on both α and n for different integer values of β. Nevertheless, *H(nT)* for non-integers values of beta is straightforward to calculate by using generic series defining the expected number of failures for any non-homogeneous Poisson process.

As the duration of the contract is $n(T+T_p)$, the expected maintenance direct cost is

$$C_M(nT) = \frac{C_p + H(nT) C_r}{n(T+T_p)}. \quad (6)$$

In addition, the expected availability during the contract as a function of maintenance interventions is

$$A_M(nT) = \frac{nT - H(nT) T_r}{n(T+T_p)}. \quad (7)$$

From a perspective biased by single interests, it is clear that the client focuses on maximizing availability, whereas the agent focuses on minimizing maintenance costs. To achieve the cooperation of both parties, the next sections describe an optimal PM interval (T) aiming to the entire chain benefit while adding the influence of the critical spares inventory.

3.2. Spare components service level

The concept of spare components service level allows incorporating the preventive maintenance policy described in the above-mentioned section. Estimation of system availability as a function of critical spare parts stock is adapted from the inventory model for repairable items developed in [18]. For sake of conciseness, a one component case is treated but the extension to multi-components is straightforward. The approach is as follows.

- The system belonging to the fleet of equipment requires I types of repairable spare components.
- The fleet size is N and the multiplicity of each type of spare components in the equipment is z_i.
- Stock level of critical spare parts is S.
- Turn-around time, as the workshop repair cycle from removal of a component until readiness to use, is T_{at}.

Table 1
Values of κ as inclusion of imperfect maintenance and finite horizon.

β	κ
1	n
2	$n^2(1-\alpha)+n\alpha$
3	$n(n-1)(n-2)(1-\alpha)^2+3n(n-1)(1-\alpha)+n$

We propose the following approach to incorporate the impact of PM interval on the critical spare parts demand to workshop. The demand $\lambda(T)$ is updated as a function of each interval T from the maintenance policy by

$$\lambda(T) = \frac{N z_i}{MTBI(T) + T_p R(T) + T_r(1-R(T))} \quad (8)$$

where $R(T)$ is the reliability function at T and $MTBI(T) = \int_0^T R(t)\, dt$ is the mean time between interventions.

Expected backorders with spares stock level S, the unfilled number of demands for not having sufficient inventory, is

$$EBO(s) = \sum_{j=S+1}^{\infty} (j-S) \frac{(\lambda(T) T_{at})^j e^{-(\lambda(T) T_{at})}}{j!}. \quad (9)$$

Expected service level of equipment given by spares stock is then

$$A_S(S) = \prod_{i=1}^{I} \left(1 - \frac{EBO_i(S_i)}{N z_i}\right)^{z_i} \quad (10)$$

where the aim is to maximize equipment availability, or analogously to minimize expected backorders, as a function of the optimal investment in critical spare part inventories.

This service level usually corresponds to the fraction of time that equipment can operate because of critical spare parts that are at hand. Nevertheless, in this indicator it has been included the maintenance policy from the critical system under contracting. In the next section, both maintenance contracts conditions and spare components service level are linked as an integrated approach.

3.3. Optimal integration of maintenance policy with spares service level

The following model provides a decision-making framework to optimally decide whether the spare components pool should be managed by the client or the agent. Taking this premise into account, the system availability of interest is that which integrates the maintenance preventive policy with the spares service level, so that

$$A(nT, S) = 1 - \prod (1 - A_M(nT))(1 - A_S(S)) \quad (11)$$

where $A_M(nT)$ is given by Eq. (7) and $A_S(S)$ by Eq. (10).

Expected global cost of spares inventory $C_G(S)$ during the contract is

$$C_G(S) = C_v(S) + C_h(S) + C_d(S) \quad (12)$$

where

- $C_v(S) = n c_u (S_0 + \sum_j S_j) \mathrm{CRF}$ is the discounted acquisition cost of investment in spare parts, where c_u is the new spare acquisition cost, i is the discount factor, and

  $$CRF = \left(\frac{i(1+i)^{n(T+T_p)}}{i(1+i)^{n(T+T_p)} - 1}\right)$$

  is the capital recovery factor across the contract horizon $n(T+T_p)$.
- $C_h(S) = n c_u (S_0 + \sum_j S_j) c_{h0} \mathrm{CRF}$ is the holding cost for keeping inventories at hand, where c_{h0} is the holding cost rate.
- $C_d(S) = c_{d0}(1 - A(nT, S)) \sum_j N_j$ is the downtime cost given by the production loss period, where c_{d0} is the downtime cost rate.

This model is capable of efficiently integrating critical spare parts stockholding with outsourcing contracts design. The main options to handle the spare components pool within the maintenance service contract are presented in the following subsections.

3.3.1. *Option 1: client manages the pool of spare parts*

Option 1 sets the contractual framework in which the client agrees to manage the pool of spare components. In this scenario, although agreement restraints, there are no major incentives for the agent to avoid an indiscriminate use of components. Following the lead of [3] and [4], profits for the supply chain can be adapted as follows.

Let $\Pi_c(nT, S)$ be the expected profit for the client. As the client manages the pool, its profit is affected by the entire spares global cost; that is, acquisition cost, holding cost, and downtime cost. Hence, this profit is

$$\Pi_c(nT, S) = rA(nT, S) - p - C_G(S). \tag{13}$$

Moreover, let $\Pi_a(nT, S)$ be the expected profit for the agent. Under this scenario, the profit for the agent is only affected by the service fee and the preventive maintenance cost. That is

$$\Pi_a(nT, S) = p - C_M(nT). \tag{14}$$

3.3.2. *Option 2: agent manages the pool of spare parts*

Option 2 sets the contractual framework in which the agent agrees to handle the pool of spare components. If so, a policy based on rational use of components turns suitable for the agent. Profits for the supply chain are the following.

Although the client does not cover the entire spares global cost, its benefit is still impacted by the related downtime cost. The expected profit for the client is therefore

$$\Pi_c(nT, S) = rA(nT, S) - p - C_d(S). \tag{15}$$

As the agent manages the pool, its benefit is affected by both acquisition cost and holding cost. The expected profit for the agent is hereby

$$\Pi_a(nT, S) = p - C_M(nT) - (C_v(S) + C_h(S)). \tag{16}$$

Ultimately, the total expected profit for the service chain $\Pi(nT, S)$ valid for both Option 1 and Option 2 is

$$\Pi(nT, S) = rA(nT, S) - C_M(nT) - C_G(S). \tag{17}$$

Using this framework, the chain coordination can be achieved by selecting the optimal joint value $[T, S]$ that maximizes $\Pi(nT, S)$. This policy profitably allocates the spare components pool, while both contracting parties obtaining higher benefits than pursuing single objectives separately.

3.4. *Coordination mechanisms for optimal joint values*

Coordination mechanisms can be used to ensure a cooperative setting under the above-mentioned Option 1 and Option 2. Following the lead of [3] and [4], subsidization bonuses on both PM intervals and spares pooling costs can be adapted to set parties' joint values $[T, S]$ with the one of the supply chain.

3.4.1. *Cost subsidization under Option 1*

When the PM interval of the agent is higher than optimal T of the supply chain, the client agrees to subsidize the direct cost of PM to create an incentive for the agent. If let ΔC_p be the PM subsidization bonus, the new preventive cost is

$$C_p' = C_p - \Delta C_p. \tag{18}$$

The expected profit for the client adding the PM bonus effect is

$$\begin{aligned}\Pi_c(nT, S) &= rA(nT, S) - p - C_G(S) - \frac{n\Delta C_p}{n(T+T_p)} \\ &= rA(nT, S) - p - C_G(S) - \frac{\Delta C_p}{T+T_p}.\end{aligned} \tag{19}$$

The expected profit for the agent adding the PM bonus effect is

$$\begin{aligned}\Pi_a(nT, S) &= p - C_M(nT) + \frac{n\Delta C_p}{n(T+T_p)} \\ &= p - C_M(nT) + \frac{\Delta C_p}{T+T_p}.\end{aligned} \tag{20}$$

With the optimal selection of ΔC_p, the agent is encouraged to adjust its PM interval as needed for chain coordination.

3.4.2. *Cost subsidization under Option 2*

Since under Option 2 the agent manages the pool, another mechanism is needed to cope with its extra acquisition and holding costs. Although similar to the aforesaid PM bonus, this model is rather based on subsidizing the spares pooling cost. The scheme creates an incentive for selecting the optimal stock level of the chain, while it keeps the benefits of adjusting the PM interval. Let Δc_u be the inventory subsidization bonus, the new acquisition cost is thus

$$c_u' = c_u - \Delta c_u. \tag{21}$$

The expected profit for the client adding the pooling bonus effect is

$$\Pi_c(nT, S) = rA(nT, S) - p - C_d(S) - \frac{\Delta C_p}{T+T_p} - \Delta c_u \left(S_0 + \sum_j S_j \right). \tag{22}$$

The expected profit for the agent adding the pooling bonus effect is

$$\Pi_a(nT, S) = p - C_M(nT) - (C_v(S) + C_h(S)) + \frac{\Delta C_p}{T+T_p} + \Delta c_u \left(S_0 + \sum_j S_j \right). \tag{23}$$

The cost subsidization models for Option 1 and Option 2 induce the agent to optimally perform both maintenance and stockholding services. Such policy ensures maximum supply chain performance.

4. Case study

In the following case study, the critical components of interest are principal alternators of a fleet of haul trucks operating in a copper mining company. This client contracts out the fleet maintenance service to a specialized agent attempting to ensure high equipment performance. The parameters for the preventive

Table 2
Parameters for the joint maintenance-stockholding model.

Management area	Parameter	Value	Unit
Preventive maintenance strategy	h_0	0.001	(1/Kh)
	β	3	
	T_p	1	(Kh)
	T_r	0.3	(Kh)
	C_p	8	(KUS$)
	C_r	0.4	(KUS$)
	r	1500	(KUS$)
	p	350	(KUS$)
	α	0.95	
	n	5	(overhauls)
Spare components stockholding	N	20	(trucks)
	z_i	1	(alternator/truck)
	T_{ot}	933	(h)
	c_u	80	(KUS$)
	c_{d0}	5.3	(KUS$/h/truck)
	c_{h0}	0.1	(1/alternator investment)
	i	0.1	

maintenance strategy and spare components stockholding are shown in Table 2.

Fig. 1 shows the system availability resulting in merging of both the availability related to maintenance strategy and the spares stockholding service level. Higher service level can be provided as the spares stock level S increases, but higher investment is required. Moreover, the optimal PM interval T changes over the associated spares stock range. Under the proposed framework, the system availability $A(nT,S)$ is clearly a performance indicator of interest and thereby it is used to coordinate the chain profits during the contract.

Figs. 2 and 3 reveal the differences in profits depending on the allocating position of the critical spare components pool. The results of the aforementioned Option 1 and Option 2 are obtained by solving Eqs. (13–17) as follows. When the client manages the pool, the joint values $[T,S]$ are $\left[18\times10^3,0\right]$ for the agent and $\left[11\times10^3,3\right]$ for the client. The corresponding single profits are $\Pi_a(nT,S)=\text{US\$ }287,888$ and $\Pi_c(nT,S)=\text{US\$ }935,142$. Conversely, when the agent manages the pool, the joint values are $\left[18\times10^3,0\right]$ for the agent and $\left[10\times10^3,10\right]$ for the client. The respective single profits are $\Pi_a(nT,S)=\text{US\$ }287,888$ and $\Pi_c(nT,S)=\text{US\$ }1,149,772$. It is considered that p is set to fulfill the profit constraint π. Before subsidization, the corresponding profits for the supply chain by using optimal parties T^* intervals are $\Pi(nT_a^*,S)=\text{US\$ }1,169,230$ and $\Pi(nT_c^*,S)=\text{US\$ }1,211,243$ for Option 1, and $\Pi(nT_a^*,S)=\text{US\$ }1,169,230$ and $\Pi(nT_c^*,S)=\text{US\$ }1,206,436$ for Option 2. However, the optimal supply chain joint value $[T^*,S^*]$ is $\left[15\times10^3,3\right]$, which leads to a higher profit $\Pi(nT,S)=\text{US\$ }1,219,018$. Therefore, the optimal duration of the contract is $n(T^*+\mathrm{T_p})=5(15+1)\times10^3=80\times10^3(\mathrm{h})$.

From the previous results, it is clear that taking into account the entire supply chain is the best possible scenario. As anticipated, the agent must be motivated to adjust its PM interval and stock as needed for chain coordination. To achieve this result, the cooperative mechanisms described in Section 3.4 are used. Under Option 1, the interval of the agent is certainly higher than desired, thus the client subsidizes the PM cost. In this case, $\Delta C_p=2.853$ sets the agent's PM interval with the optimal interval of the chain, namely from $T=18\times10^3$ to 15×10^3. Under Option 2, it is clear that the agent attempts to keep the stock level as low as possible since the extra acquisition and holding costs. Hence, the client decides to subsidize those significant inventory costs. In this case, $\Delta c_u=55.030$ sets the stock level with the optimal stock of the chain.

After subsidization, profits for the whole supply chain by using optimal single intervals align with the maximum value $\Pi(nT,S)=\text{US\$ }1,219,018$. Nonetheless, as expected, the single profits change across options. For example, the client's profit decreases from US\$935,142 (Option 1) and US\$1,149,772 (Option 2) to US\$915,065 due to the subsidization mechanism, and the agent's profit increases from US\$287,888 to US\$303,953. For further details on changes for both subsidization options, Figs. 4 and 5 denote a sensitivity analysis for those optimal joint values that maximize the profit for the entire channel. Note that after the application of both bonuses, the joint values of agent and

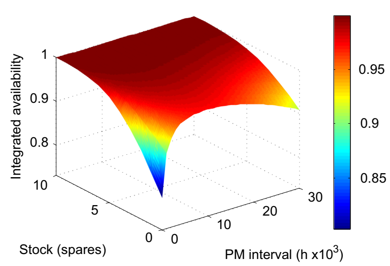

Fig. 1. System availability by integrating T and S.

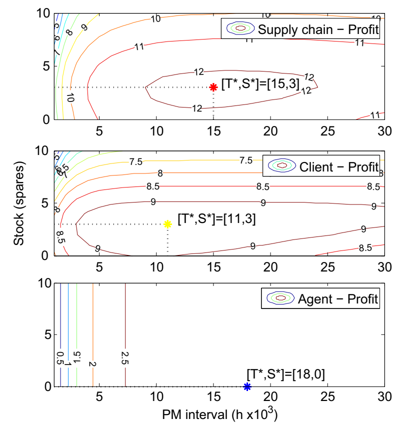

Fig. 2. Study of optimal T and S when the client manages the pool of spare components.

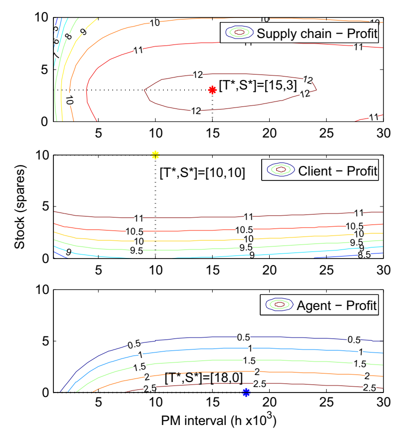

Fig. 3. Study of optimal T and S when the agent manages the pool of spare components.

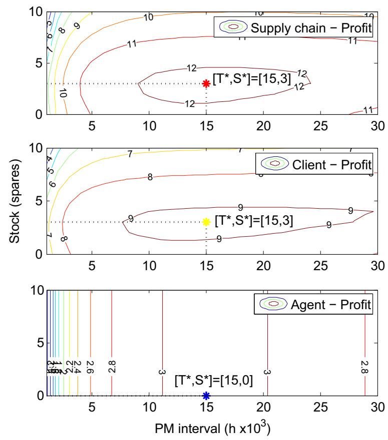

Fig. 4. Study of optimal T and S when the client subsidizes the PM cost of the agent.

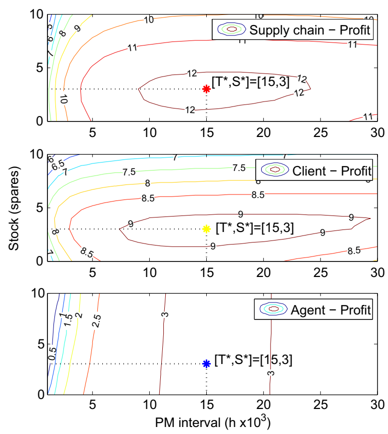

Fig. 5. Study of optimal T and S when the client subsidizes both acquisition and holding costs of the agent.

contractor align with the optimal joint value of the supply chain [15×10^3, 3]. Hence, the desired coordination is achieved. As demonstrated, the supply chain benefit is higher than those single profits obtained by the contracting parties. Consequently, the proposed framework motivates both chain parties to improve their maintenance and supply services continuously.

5. Conclusions

This paper has introduced a model for defining the optimal manager of the pool of components within outsourcing services. A decision-making framework has been provided to integrate preventive maintenance with critical spares stockholding for contract profitability. Using an imperfect maintenance strategy over a finite horizon, the allocation scheme induces the parties involved to perform maintenance and supply activities cooperatively, rather than a separated non-optimal way. This aim is achieved by setting an original joint value consisting of the preventive maintenance interval and the spare parts stock level that maximizes the total expected profit for both client and agent.

It has been found that the joint values reach the supply chain coordination for the two options under study, when the client administers the spare components and when the agent is the pool manager. However, there are scenarios where the expected profit is not sufficient to drive changes in the policy. To provide an incentive to set parties' joint values with the optimal benefit of the supply chain, subsidization bonuses on both additional PM performed and spares pooling costs are practicable methods. The procedure to estimate such bonuses has been developed.

Finally, we have demonstrated that the model is capable of coordinately optimizing business performance for the entire supply chain. Both client and agent are encouraged to continually improve their maintenance services and supply practices, thus obtaining higher joint benefits compared to those single profits when no coordination occurs. Accordingly, this research has built an interesting bridge between the decision areas of preventive maintenance strategy and spare parts management.

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Critical spare parts ordering decisions using conditional reliability and stochastic lead time

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ABSTRACT

Asset-intensive companies face great pressure to reduce operation costs and increase utilization. This scenario often leads to over-stress on critical equipment and its spare parts associated, affecting availability, reliability, and system performance. As these resources impact considerably on financial and operational structures, the opportunity is given by demand for decision-making methods for the management of spare parts processes. We proposed an ordering decision-aid technique which uses a measurement of spare performance, based on the stress–strength interference theory; which we have called *Condition-Based Service Level* (CBSL). We focus on *Condition Managed Critical Spares* (CMS), namely, spares which are expensive, highly reliable, with higher lead times, and are not available in store. As a mitigation measure, CMS are under condition monitoring. The aim of the paper is orienting the decision time for CMS ordering or just continuing the operation. The paper presents a graphic technique which considers a rule for decision based on both condition-based reliability function and a stochastic/fixed lead time. For the stochastic lead time case, results show that technique is effective to determine the time when the system operation is reliable and can withstand the lead time variability, satisfying a desired service level. Additionally, for the constant lead time case, the technique helps to define insurance spares. In conclusion, presented ordering decision rule is useful to asset managers for enhancing the operational continuity affected by spare parts.

1. Introduction

Decision-making processes are crucial for organizations within a scenario of intense competitiveness. Since companies are frequently required to reduce production costs and increase asset utilization, misguided decisions may lead to over-stress on equipment. This situation affects reliability and, more importantly, system throughput. Continuous improvement of the ability to add value and enhance profitability of operations is needed by firms in pursuit of performance excellence [1]. An efficient resources ordering is indispensable to achieve significant availability exigencies of equipment-intensive industries, such as mining, aeronautic, nuclear energy, or defence. This equipment is supported by spare parts inventories, which are particularly relevant considering the influence of stock-outs on downtime [2]. Appropriate spare parts allocation decisions are therefore essential to system performance of these industries.

Spare parts play a fundamental role in the support of critical equipment. In a typical company, approximately one third of all assets corresponds to inventories [3]. Of these assets, critical spare parts have special relevance because they are associated with both significant investment and high reliability requirements. As an example, spares inventories sum up above US$ 50 billion in the airlines business [4]. The mismanagement of spare parts that support critical equipment conduces to considerable impacts on financial structure and severe consequences on operational continuity. The improvement of key profits on both logistics and maintenance performance can be achieved by inventory management of costly components, which have extremely criticality on equipment-intensive industries [5]. Therefore, efficient decisions about spare-stocking policies can become essential in the cost structure of companies. In order to provide an efficient spare management performance, a suitable ordering strategy can be relevant. A spare part classification scheme becomes necessary to set optimal policies for those spares that may affect the system the most, and at the least effort. We proposed an ordering decision-aid method to secure the spare management performance into an operational environment that needs continuity to compete into a demanding business context.

1.1. Critical spare parts and maintenance strategy

The need for spare parts inventories is dictated by maintenance actions [6]. In addition, maintenance strategy can be treated by

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Figure B.2: **Paper II**. Corresponding author: David R. Godoy Ramos

Condition-Based Maintenance (CBM). In this case, models incorporate information about equipment conditions in order to estimate the conditional reliability. This information comes from, for instance, vibrations measurements, oil analysis, sensors data, operating conditions, among others. These measures are called covariates. Covariates may be included on the conditional reliability using the Proportional Hazards Model (PHM) [7], which allows combining age and environmental conditions. In the interaction between operational environment and equipment, while age can be relatively easy to notice, deterioration can be measured by conditions assessment [8]. Therefore, CBM becomes useful to set maintenance policies even with different levels of monitoring restrictions. Compared to usual time-based maintenance strategies, condition monitoring systems offer significant potential to add economic value to spares management performance [9]. Particularly, this paper uses CBM models to calculate conditional reliability in order to make ordering or replacement decisions.

Lead time is another important aspect to consider in spare parts ordering. The random time between fault event and the actual component failure may cause system performance deteriorations [10]. Nonetheless, it also provides a opportunity window to set replacement policies. Logistically, there are also delays between the order of spares and their arrival [11]. This situation is even more crucial when spare parts are critical, since they are not always available at the supplier store. Customs delays and the need of special transport are a source of significant lead times; moreover, when dealing with complex equipment parts made to order, lead times may exceed a year [12]. The lack of these items because of a delay in delivery (and their consequent installation) may have severe consequences in the operational continuity.

The core of this paper is on those critical spare parts that affect production, safety, are expensive, highly reliable, and usually are associated with higher lead times. These items are critical too, when they support equipment which is essential in an operational environment [2]. Henceforward, all spare parts that meet these characteristics will be called, "Condition Managed Critical Spares", or just CMS. Fig. 1 shows a diagram with the spare parts that we are focusing on. CMS are repairable, however their repair times are slower than supplier lead times, this particularity turns these CMS into non-repairable spare parts for the purposes of this model. As CMS are not available in store, CMS condition is monitored as a mitigation measure to its criticality in the operation. Justification for not having them in store lies in the expectation that the CBM models will predict failures with sufficient lead time to overcome the need for spare-stocking.

Previous works have treated the decision-making process using CBM, for instance: research deals with a continuously deteriorating system which is inspected at random times sequentially chosen with the help of a maintenance scheduling function [13]. There is also research obtaining an analytical model of the policy for stochastically deteriorating systems [14]. However, spare parts issues are not included on those papers. Furthermore, there are several researches for CBM policies that consider unlimited spare parts which always are available [15]. Nevertheless, the focus of this paper is on critical spare parts which are, precisely, not available in store. According to [16], few existing ordering and replacement policies are proposed in the context of condition-based maintenance. In fact, the work described by [16] aims to optimize CBM and spare order management jointly. Other works [17,18] consider optimal ordering and replacement policy of a Markovian degradation system under complete and incomplete observation, respectively. However, the difference between this paper and the works stated above is the need to install a user-friendly technique to decision-making process for asset managers in order to improve the spare parts management considering the unique characteristics of CMS. In accordance with current industrial requirements, a graphical tool of this type could be easy to implement. Spare parts estimation based on reliability and environment-operational conditions is a method to improve supportability. This method can guarantee non-delay in spare parts logistics and to improve production output [19].

1.2. *Spare management performance: condition-based service level*

There are several definitions to measure spare management performance. According to [20] three obvious indicators are ready rate, fill rate, and units in service. Ready rate is the probability that an item observed at a random point in time has no back orders (back order is considered as any demand that cannot be met from stock). Fill rate is defined as the expected number of units demanded per time period for an item that can be immediately satisfied from stock at hand. Meanwhile, units in service are the expected number of units in routine resupply or repair at a random point in time. The work stated by [2] uses the instantaneous reliability of stock term as one of its criteria for determining an optimal stock level. Instantaneous reliability is defined as the probability of a spare being available at any given moment in time. This measurement can be equivalent to fill rate. In spite of these valuable definitions, the spare part reliability concept used in this paper is significantly different. The source of this distinction is given by the critical nature of spare parts which are considered in this paper, specially its uniqueness characteristic. Usually, these kinds of critical spare parts are not available in store, thus a common concept such as fill rate is not completely applicable.

For the latter reason, it seems appropriate to introduce a new concept which we have called as "Condition-Based Service Level" (CBSL). CBSL is based on the stress–strength interference theory [21]. This theory considers two main variables: a stress which is any load applied on a system and that may produce a failure (in this case, depletion on service level), and a strength which is the maximum value that system can withstand without failing. Therefore, CBSL is defined as the probability that the stress does not overcome the strength. Stress–strength interference models are widely applied in component reliability analysis [22]. Due to the model ability to be used when probability distributions are known and, also, both stress and strength could be general in meaning [22], it is possible to adapt a version. For purposes of this paper, stress can be represented by lead time and strength by conditional reliability.

The paper presents a graphic method which uses CBSL as key indicator, to achieve an effective policy to define the suitable time for CMS ordering, through a rule decision based on both condition-based reliability function and a stochastic/fixed lead time. The aim of the paper is orienting the decision about CMS ordering or to continue the operation process without ordering. The reliability threshold can be chosen by each company according to their own needs of service level.

Having introduced the importance of CMS ordering process in the context of operational continuity, the rest of the paper is organized as follows: Section 2 indicates the model formulation. Section 3 shows the associated case study. Finally, Section 4 reveals the conclusion of the work.

2. Model formulation

In order to precise the CMS ordering decision-making, it is necessary to estimate the conditional reliability and add the influence of lead times. The following items define the calculation methodology of these aspects.

2.1. *Conditional reliability model*

For the sake of self-containment, we describe in detail relevant elements which are developed in [23,24]. Reliability function is based primarily on the Markov Failure Time Process model. The reliability

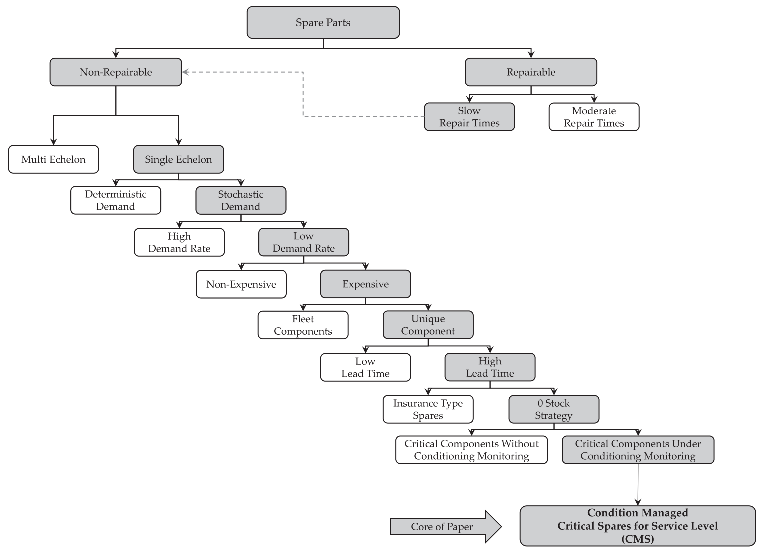

Fig. 1. Condition managed critical spares.

function of an item can be defined as the probability of survival after a certain interval of time t. For the conditional case (namely, assuming that item has been operated by a time x), the probability of interest is $P(T>t|T>x)$, where T is the equipment lifetime. This reliability is interesting in CBM, given that it is assumed that the item has been operated until the inspection moment [2]. It is assumed that hazard rate can be incorporated into the model using PHM, e.g. [7,25,26]. This method is widely accepted in order to incorporate condition data of equipment [2] (as used in CBM). Hence

$$\lambda(t)=\lambda(t,Z(t))=\lambda_0(t)e^{\sum_i \gamma_i Z_i(t)} \quad (1)$$

where $\lambda_0(t)$ is a baseline hazard rate, while γ_i is the weight of each time-dependent covariate $Z_i(t)$. For the present paper, a Weibull-PHM was used, thus the hazard rate is

$$\lambda(t)=\lambda(t,Z(t))=\frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1}e^{\sum_i \gamma_i Z_i(t)}, \quad t\geq 0 \quad (2)$$

The use of Non-Homogeneous Markov Process (NHMP) is of particular interest in applications of CBM [2,24]. Transition probabilities (from a state i to a state j, of covariates under study) can be defined as

$$L_{ij}(x,t)=P(T>t,Z(t)=j|T>x,Z(x)=i), \quad x\leq t \quad (3)$$

where T is a random variable representing the failure time of the item. Note that covariates $Z(x)$ can be discretized within intervals using values ranges for a finite number of states: $0,1,2,\ldots,s$. For example, if the condition under study is the oil level of a motor, the states could be described through intervals with levels limits as: "low", "normal", and "dangerous".

Thus, it is possible to find a relationship between hazard rate and transition probabilities $L_{ij}(x,t)$ [24]. The reliability of interest can be obtained combining both concepts (conditional probability and PHM).

The reliability at time t, given that the spare has survived until a time x, and at that time x the condition is $Z(x)=i$, is given by

$$R(t|x,i)=P(T>t|T>x,Z(x)=i)=\sum_j L_{ij}(x,t), \quad x\leq t \quad (4)$$

If the matrix $\mathbf{L}(x,t)=[L_{ij}(x,t)]$ is defined and it is assumed that $\mathbf{L}(x,x)=\mathbf{I}$ (where $\mathbf{I}$ is the identity matrix), the Markov property can be used [24].

Then, it is demonstrable that all functions $L_{ij}(x,t), x\leq t$ satisfy the system of equations [23]:

$$\frac{\partial}{\partial t}\mathbf{L}(x,t)=\mathbf{L}(x,t)\mathbf{L}(t)=\mathbf{L}(x,t)(\mathbf{\Lambda}(t)-\mathbf{D}(t)) \quad (5)$$

Let

- $\mathbf{\Lambda}(t)=[\lambda_{ij}(x)]$ is the matrix of transition rates. The transition rates $\lambda_{ij}(x)$ can be estimated using the approach of [23].
- $\mathbf{D}(t)=[\lambda(t,i)\delta_{ij}]$ is a diagonal matrix, with $\delta_{ij}=p_{ij}(x,x)$ (i.e., it takes the value 1 when $i=j$, and the value 0 when $i\neq j$). For this particular case, $\mathbf{D}(t)=[(\beta/\eta(t/\eta)^{\beta-1}e^{\sum_i \gamma_i Z_i(t)})\delta_{ij}]$.

In order to solve the system of equations described in Eq. (5), two cases are identified [24]:

(i) Case I: If the failure rate is only a function of the condition process, namely $\lambda(t)=g(Z(t))$. Then, the solution is given by

$$\mathbf{L}(0,t)=e^{(\mathbf{\Lambda}-\mathbf{D})t} \quad (6)$$

(ii) Case II: If the failure rate is a function of age and current condition state, namely: $\lambda(t) = g(t, Z(t))$. Then, the solution can be approximated for the following method called "product-property".

$$\mathbf{L}(k\Delta, m\Delta) \approx \prod_{i=k}^{m-1} \tilde{\mathbf{L}}[i] \tag{7}$$

where

$$\tilde{\mathbf{L}}[k] = e^{-\int_{k\Delta}^{(k+1)\Delta} \mathbf{D}(t)\,dt} e^{\mathbf{\Lambda}\Delta} \tag{8}$$

Δ defines the approximation interval length, such that $k\Delta \le x \le (k+1)\Delta$ and $(m-1)\Delta \le t \le m\Delta$, $k < m$ [2]. In general, while the value of Δ is smaller, the precision of the reliability estimation is better [24] (but also the amount of iterations will be larger).

The stated Case II corresponds to Weibull-PHM model used in this paper, because of it depends on age and condition. Then, the "product-property" method was used in order to estimate the matrix of transition probabilities, and consequently, the reliability function. In [24] also is defined other method to estimate the solution of the system of Eq. 5 called "product-integral" method. However, the "product-property" method is more accurate than the "product-integral" method when larger values of Δ are used. Besides, the "product-property" method is convenient because it requires the estimation of only one transition matrix.

2.2. Condition-based service level (CBSL)

CBSL could be estimated adapting the structure given by stress–strength interference theory [21]. Let x be the stress random variable and $f(x)$ be its probability density function. Likewise, let y be the strength random variable and $f(y)$ be its probability density function. Therefore, the probability that stress does not exceed an x_0 value is

$$P(x \le x_0) = F_x(x_0) = \int_0^{x_0} f_x(x)\,dx \tag{9}$$

Also, the probability that strength does not exceed an y_0 value is

$$P(y \le y_0) = F_y(y_0) = \int_0^{y_0} f_y(y)\,dy \tag{10}$$

In order to calculate CBSL, this paper recognizes lead time as equivalent to stress and conditional reliability as equivalent to strength. While conditional reliability is estimated using the model described in Section 2.1, the work adds the effect of lead time considering two cases described by [21]: (i) stochastic lead time (stress) and stochastic conditional reliability (strength), and (ii) constant lead time (stress) and stochastic conditional reliability (strength).

2.2.1. Stochastic lead time and stochastic conditional reliability

If both variables are stochastic, CBSL is the probability that lead time (stress) is less than conditional reliability (strength). Or equivalently, the probability that conditional reliability exceeds lead time. As a result, CBSL is given by

$$CBSL = P(x \le y) = \int_0^{\infty} \left[\int_0^{y} f_x(x)\,dx \right] f_y(y)\,dy = \int_0^{\infty} F_x(y) f_y(y)\,dy \tag{11}$$

Fig. 2 exhibits the CBSL which is defined by the area where both tail curves overlap or interfere with each other. This interference analysis between stress and strength is the reason of the theory name.

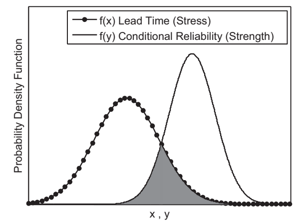

Fig. 2. CBSL as overlap of conditional reliability and lead time.

2.2.2. Constant lead time and stochastic conditional reliability

If the lead time is a known constant value x_s and conditional reliability is a random variable, then CBSL is the probability that conditional reliability exceeds the constant lead time. Hence

$$CBSL = P(y \ge x_s) = \int_{x_s}^{\infty} f_y(y)\,dy \tag{12}$$

Consequently, this instance could be considered as a special case of when both stress and strength are stochastic.

2.3. Spare part ordering decision rule

Considering a deterministic lead time L, spare part ordering time T_o is defined by time T_{th} at which desired reliability threshold R_{th} is reached. Note that often a constant lead time is not the case and variations on the delivery time exist [25]. Companies can choose several scenarios of reliability threshold in order to obtain a given service level. Therefore, the decision rule can be described by

$$T_o = \inf\{t \ge 0 : L \ge T_{th}\} \tag{13}$$

Fig. 3 illustrates this rule. It uses data from a numerical example given by [24]. If lead time L is less than T_{th} at a given inspection time t (case shown by L_1) then equipment can continue operating with the same spare part, because there is enough time until the arrival of a new spare faced with a potential need (because of the policy to keep reliability R_{th}). If lead time L is greater than T_{th} (case shown by L_2) then an ordering decision is required, otherwise spare part will not be able to ensure the operational continuity of the equipment supported by the spare-stocking. If lead time L and T_{th} are equal then an ordering decision must be also made, because this situation is likely to require a setup time for the new spare part.

3. Case study

3.1. Condition-based reliability

The following case is an adapted version of a case study described by [25]. The spare of interest is an electric motor of a mining haul truck and, based on expert judgement, oil is the key factor to model the condition process. Table 1 describes the model parameters. Covariates were discretized in three bands, as shown in Table 2. In addition to, Table 3 indicates the estimated matrix of transition probabilities.

The conditional reliability function can be estimated for the 3 different initial states of oil by using the methodology indicated in Section 2.1. As an example, Fig. 4 shows the conditional reliability for State 0. Working ages have been set in operational hours (h).

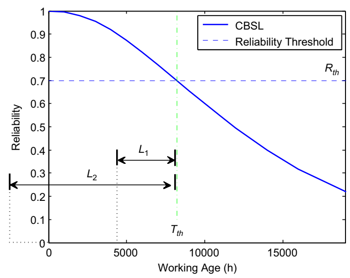

Fig. 3. Spare part ordering decision rule.

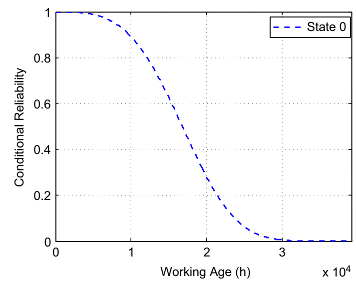

Fig. 4. Conditional reliability function at oil initial state.

Table 1
Baseline hazard rate parameters.

Parameter	Value	Units
β	3.5	
η	19,003	(h)
γ	0.0001742	(ml/particles)

Table 2
Oil initial system states and covariate bands.

Initial state	Covariate band (ml/particles)	State value (particles/ml)
State 0	(0…53.73)	7
State 1	(53.73…87.91)	76.5
State 2	(87.91…∞)	11,586

Table 3
Transition probabilities for motor condition.

j	1	2	3
p1-j	0.99797	0.00202	0.00001
p2-j	0.00159	0.99832	0.00009
p3-j	0.00317	0.00181	0.99505

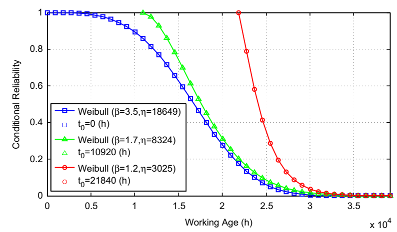

Fig. 5. Weibull model fit for conditional reliability at different initial survival times.

Conditional reliability is fitted with a Weibull distribution for different initial survival times ($t_0 = 0$ (h) or 0 (months), $t_0 = 10,920$ (h) or 12 (months), and $t_0 = 21840$ (h) or 24 (months). Fig. 5 displays the model fit. A Kolgomorov–Smirnov test was applied to prove the model and the results were satisfactory.

Having set the Weibull distribution for conditional reliability and considering the CBSL definition, the two cases mentioned in Section 2.2 are tested. Firstly, the case where both lead time (stress) and conditional reliability (strength) are stochastic. Secondly, the case where conditional reliability is stochastic, but lead time is constant.

3.2. Condition-based service level considering stochastic lead time

We test using different distributions for lead time (including constant lead time in next section). In this sense, the aim is determining the capability to withstand lead time variability. The choice of any lead time distribution is defined by delivery constraints of spare part supplier. Fig. 6 exhibits four distributions which are considered to fit lead time, namely: exponential, truncated normal, Weibull with 2 parameters (Weibull (2p)), and Weibull with 3 parameters (Weibull (3p)). The same mean is set for all distributions. With an estimated operational utilization of 80%, 1 operational week is equivalent to 210 operational hours (h). In this case, mean lead time is set at 2730 (h) (equivalent to 13 weeks or 3 months).

Fig. 7 exhibits a performance realization as a result of evolution over time (t) because of interaction between conditional reliability and lead time. Conditional reliability has been fitted as a Weibull (2p) distribution. Fig. 8 is a top view of the same realization which illustrates that CBSL (probability that strength is greater than stress) is declining as the conditional reliability decreases. In other words, component is becoming older over time because the evolution of condition, thus service level is also declining. Figs. 9–12 show the values of CBSL for different scenarios of mean lead time and for different initial survival times. Standard deviation depends on each distribution.

If CBSL is greater than a given reliability threshold R_{th}, then the system is able to resist stress satisfying the desired service level. Thus, equipment can continue operating and a spare part order is not necessary. On the other hand, if CBSL is less than R_{th}, then a spare part order is mandatory because of spare part will not be able to withstand the lead time variability, and the desired reliability would not be accomplished.

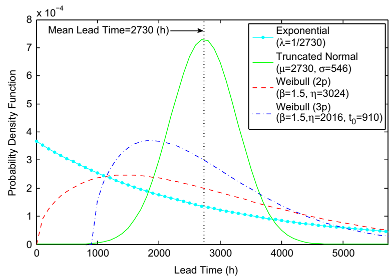

Fig. 6. Probability density functions versus lead time.

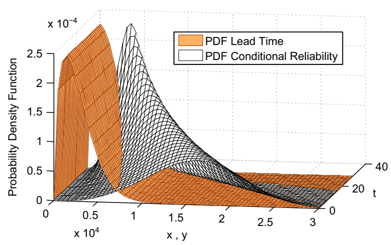

Fig. 7. Performance realization of stress versus strength.

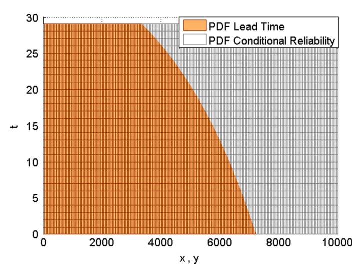

Fig. 8. Top view of CBSL for a given realization.

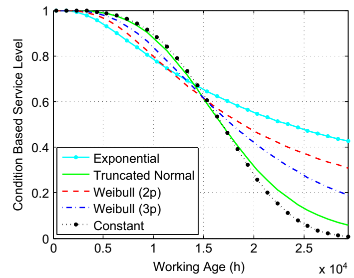

Fig. 9. CBSL for initial survival time of 0 months.

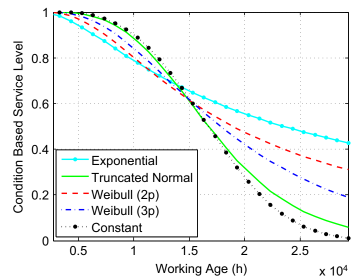

Fig. 10. CBSL for initial survival time of 3 months.

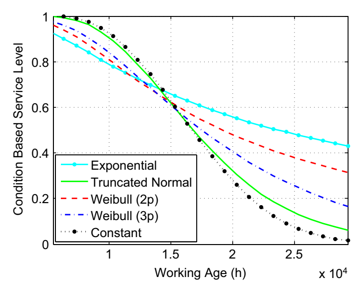

Fig. 11. CBSL for initial survival time of 6 months.

3.3. Condition-based service level considering constant lead time (special case)

Table 4 evidences the decision-making for different reliability thresholds and their respective working ages, where spare part ordering depends on the decision rule (Section 2.3). In the current case, three threshold values are considered, namely: 99%, 95%, and 90%. Three lead time scenarios in order to realize the effect of them on service level are considered. Markov reliability model allows setting any initial condition for spares. In this regard, a complete range of practical operational environments can be represented. For example, if it is assumed that the motor is new, then the initial condition is "as-good-as new" ("State 0").

As expected, when lead time is increasing, reliability constraints are more demanding and ordering decision time turns sooner. As shown in Table 4, for a reliability threshold of 95%, the decision changes from "continue" without ordering to "order" the spare, when the lead time increases from 847 (h) to 3388 (h). On the other hand, initial condition states also play a role. For a lead time of 1694 (h) and at the same reliability threshold of 95%, a greater deterioration level makes to change the decision from "continue" to "order".

Working age of this decision map makes practical sense until approximately 6 months of expected lead time. If lead time is greater than that period, then it could be better to stock spare parts. However, CMS are unique and are not backed-up. Therefore, another important factor is when the component becomes older. Fig. 13 demonstrates this situation, considering different scenarios of η to a situation of increasing aging. Table 5 displays the same decision map but considering $(2/3)\eta$ from the original value.

Using new η, the situation becomes critical at a lower time. With the original model, the scenario of "always ordering" happened just at 6 months. With new η, the decision of "always ordering" should be already made with any initial state at 3 months. This is relevant because if lead time is 6 months, spare parts should be purchased as soon as the component starts to operate. Then, with this map is also possible to visualize those parts that can be classified as insurance spares.

4. Conclusions

This work provides a technique to enhance spare parts ordering decision-making when companies need to ensure a reliability threshold restricted by a lead time. Case study showed that condition data could be an accurate indicator of component state affecting the shape of reliability function. The ordering process can be affected by different initial survival times and initial condition states; they can change the decision for same reliability threshold even. On the other hand, lead time is a relevant factor in ordering decision. The ordering policy is sensitive to different scenarios of lead times; they can also modify the spare part ordering decision if the aim is ensuring the operational continuity of the equipment supported by the spare part stock. It was concluded that, in order to fulfill with operational continuity, condition data can be a powerful tool for including in spare management. The need of focus on critical spares and severe consequences on equipment performance, demands a friendly technique which can be used in an environment where decisions are needed quickly, in this regard, the presented decision rule is easy to implement graphically and it can be used by asset managers to enhance operational continuity.

Future works may include a combination of CBSL with associated maintenance and logistics costs in order to obtain a global perspective of asset management.

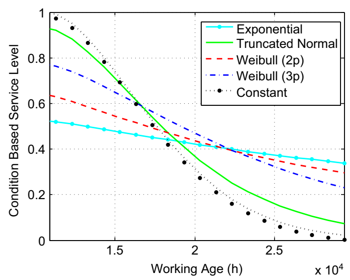

Fig. 12. CBSL for initial survival time of 12 months.

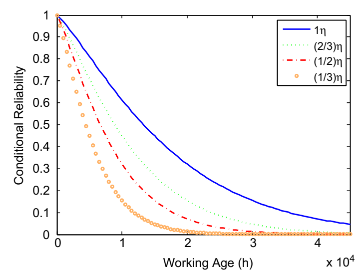

Fig. 13. Conditional reliability considering aging by depletion of η.

Table 4
Motor ordering decision for different reliability thresholds, considering several lead time scenarios.

Reliability threshold (%)	Expected time (h)			Ordering decision		
	State 0	State 1	State 2	State 0	State 1	State 2
Expected lead time = 910 (h) (1 month).						
99	494	467	122	**Order**	**Order**	**Order**
95	1753	1723	1067	Continue	Continue	Continue
90	3100	3074	2518	Continue	Continue	Continue
	Expected time to order (h)					
Expected lead time = 2730 (h) (3 months)						
99	494	467	122	**Order**	**Order**	**Order**
95	1753	1723	1067	Continue	Continue	**Order**
90	3100	3074	2518	Continue	Continue	**Order**
	Expected time to order (h)					
Expected lead time = 5460 (h) (6 months)						
99	494	467	122	**Order**	**Order**	**Order**
95	1753	1723	1067	**Order**	**Order**	**Order**
90	3100	3074	2518	**Order**	**Order**	**Order**

Table 5
Motor ordering decision for different reliability thresholds, considering several lead time scenarios.

Reliability threshold (%)	Expected time (h)			Ordering decision		
	State 0	State 1	State 2	State 0	State 1	State 2
Expected lead time=910 (h) (1 month).						
99	284	283	227	**Order**	**Order**	**Order**
95	1074	1068	917	Continue	Continue	Continue
90	1905	1897	1691	Continue	Continue	Continue
	Expected time to order (h)					
Expected lead time=2730 (h) (3 months)						
99	284	283	227	**Order**	**Order**	**Order**
95	1074	1068	917	**Order**	**Order**	**Order**
90	1905	1897	1691	**Order**	**Order**	**Order**
	Expected time to order (h)					
Expected lead time=5460 (h) (6 months)						
99	284	283	227	**Order**	**Order**	**Order**
95	1074	1068	917	**Order**	**Order**	**Order**
90	1905	1897	1691	**Order**	**Order**	**Order**

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C. COVER PAGES OF ISI JOURNAL ARTICLES

The cover pages of the ISI articles published up to the Thesis submitting date are provided below.

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A decision-making framework to integrate maintenance contract conditions with critical spares management

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ABSTRACT

Maintenance outsourcing is a strategic driver for asset intensive industries pursuing to enhance supply chain performance. Spare parts management plays a relevant role in this premise since its significant impact on equipment availability, and hence on business success. Designing critical spares policies might therefore seriously affect maintenance contracts profitability, yet service receivers and external providers traditionally attempt to benefit separately. To coordinate both chain parties, we investigated whether the spare components pool should be managed in-house or contracted out. This paper provides a decision-making framework to efficiently integrate contractual conditions with critical spares stockholding. Using an imperfect maintenance strategy over a finite horizon, the scheme maximizes chain returns whilst evaluating the impact of an additional part to stock. As result, an original joint value – preventive interval and stock level – sets the optimal agreement to profitably allocate the components pool within the service contract. Subsidization bonuses on preventive interventions and pooling costs are also estimated to induce the service provider to adjust its policy when needed. The proposed contractual conditions motivate stakeholders to continuously improve maintenance performance and supply practices, thus obtaining higher joint benefits.

1. Introduction

Maintenance outsourcing is a strategic means to improve business performance. Outsourcing creates value through the use of external resources by and for companies to acquire and sustain competitiveness [1]. The maintenance function is a main driver of outsourcing since it has excellent potential to achieve cost benefits and enhance performance among partners [2]. This business purpose is meaningful for asset intensive industries – such as mining, aeronautic, or defence – which face substantial investment in maintaining complex equipment and high demand on system availability. For these firms, the main reasons to contract out maintenance tasks rather than perform them in-house are focusing on core business, accessing highly specialized services at competitive costs, and sharing risks [2–5]. When dealing with outsourcing, effective supply chain coordination allows achieving a rewarding situation for all stakeholders [3]. Accordingly, a model capable of coordinately optimizing performance can lead to successful maintenance contracting strategies in capital intensive environments.

Spare parts management has a critical role toward operational efficiency of asset intensive industries. Equipment criticality is defined by the most relevant assets that efficiently and safely sustain production [6]. The operation of such equipment is consequently supported by critical spare parts [7]. Major spare components are related to considerable investment, high reliability requirements, extended lead times, and plant shutdowns with important effects on operational continuity [8]. A method to prevent production loss events is having inventories at hand, especially when either target service levels or backorder penalties are large [9]. This is the case of capital intensive firms, wherein critical spares storage is directly linked to business success due to the impact of stock-outs on assets utilization [7]. As an example, the aviation supply chain holds a remarkable US$ 50 billion in spares inventories to provide availability service [10]. Efficient critical spares stockholding is therefore essential for companies in which success strongly depends on equipment performance.

Maintenance contracts profitability can be significantly affected by critical spares policies. Particularly, the stock of critical repairable spares can be interpreted as a pool of components from where replacements are satisfied [7]. Consistently with the serious impact on operational and financial performance, managing the pool of critical spare components becomes a key to improve profits within the service contract. Nevertheless, as it depends

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Figure C.1: Cover page of **Paper V**. Corresponding author: David R. Godoy Ramos

Applied Stochastic Models in Business and Industry

Research Article

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Optimizing maintenance service contracts under imperfect maintenance and a finite time horizon

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When a company decides to outsource a service, the most important reasons for doing so usually are to focus on core business, to be able to access high-quality services at lower costs, or to benefit from risk sharing. However, service contracts typically follow a structure whereby both owner and contractor attempt to maximize expected profits in a noncoordinated way. Previous research has considered supply chain coordination by means of contracts but is based on unrealistic assumptions such as perfect maintenance and infinite time-span contracts. In this work, these limitations are overcome by defining the supply chain through a preventive maintenance strategy that maximizes the total expected profit for both parties in a finite time-span contract. This paper presents a model to establish such conditions when maintenance is imperfect, and the contract duration is fixed through a number of preventive maintenance actions along a significant part of the asset life cycle under consideration. This formulation leads to a win–win coordination under a set of restrictions that can be evaluated a priori. The proposed contract conditions motivate stakeholders to continually improve their maintenance services to reach channel coordination in which both parties obtain higher rewards. Copyright © 2012 John Wiley & Sons, Ltd.

Keywords: maintenance; service contracts; imperfect maintenance; finite time horizon

1. Introduction

The introduction of standards such as PAS-55 [1] and ISO 14001 [2] and the increasing concern on sustainably managing of life cycle costs has intensified the use of asset management techniques to estimate resources from system design to operation and disposal [3, 4]. One way to achieve this is to balance in-house resources and to outsource business functions such as maintenance.

Before the 1970s, most equipment maintenance was performed with in-house resources. Nevertheless, because the systems have been growing in complexity, it is more competitive to supply system service using specialized external agents and equipment [5]. In the past decade, maintenance outsourcing has significantly increased in relevance. Outsourcing has become a business key to reach a competitive advantage because products and services can be offered by outside suppliers in a more efficient and effective way [6]. There has also been a paradigm shift in asset management, in which maintenance has evolved from a cost-generating activity to a value-adding function; currently, outsourcing is viewed not only as a way to ensure cost objectives but also as a way to access better quality of service and improve the product delivery capability [7]. Outsourcing also involves risk transfer. The cost of this transfer may be estimated as the difference between outsourcing a task and performing it in-house [8]. Through maintenance externalization, a set of advantages is obtained for the manufacturer, namely (i) best maintenance practices due to expertise of the providers and use of the latest maintenance technology, (ii) risk mitigation of high costs by setting for-purpose service contracts, (iii) reduction of capital investments, and (iv) ability of in-house managers to spend more time in the strategic aspects of the business. On the contrary, some disadvantages are (i) cost of contracting scarce services, making it possible for the contractor to increase monopolistic behavior, (ii) a potentially risky dependency, such as control of machine availability transferred to a contractor,

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Figure C.2: Cover page of **Paper IV**. Co-author: David R. Godoy Ramos

Value-based optimization of intervention intervals for critical mining components

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Abstract

Highly competitive industries, such as mining, face constant pressure for continuous improvement. This increasing need for efficiency demands the use of models of reliability and benefit, especially for significant investment equipment and components. Critical major components -*e.g.* mill liners, shovel swing transmissions or haul truck engines- are related to lengthy shutdowns with a considerable impact on the financial structure. In this context, cost optimization is a widely-used principle to schedule component replacements. However, this practice traditionally involves not considering external factors of interest, such as business-market conditions, which can radically change decisions. To overcome this limitation, we have proposed a criterion based on the estimation of revenues -under several commodity price scenarios- at both the component intervention epoch and time-window during major shutdowns. The aim of this work is to guide the decision about the best epoch to replace, considering the maximization of value-adding rather than simply minimization of costs. The paper presents a model to evaluate such optimal value by estimating the net benefit subject to certain interest rate for discounting, considering the copper price, component survival probabilities (using Condition-Based Maintenance, CBM), cost and expected downtime. Results show the influence of business objectives to identify the real value of waiting the right epoch to perform an intervention, in order to optimize the decision benefit, satisfying both reliability constraints and time-windows. In conclusion, business profitability opportunities increase when maximization of value-adding is included as part of a complete view of asset management system.

Keywords: Value-based optimization, Critical components, Optimal replacement.

1. Introduction

Value-adding requires enriched methods for enhancing efficiency, reliability and profitability of decision-making processes. Continuous improvement of performance is required by the increasing competitiveness in which companies are currently involved. Desired and sustainable outcomes can be accomplished through an optimal approach of managing assets [1, 2]. Asset Management has evolved from having a narrow purpose of just fixing broken items, to a strategic wider role covering the whole life cycle system and securing future maintenance requirements [3]. This perspective creates a need for excellent practices. Maintenance excellence pursues exceptional plant efficiency by means of balancing performance, risk, and cost within a random-nature industrial environment [4]. Accordingly, competitive industries cope with an unceasing exigency to add value in their processes.

Growing business performance targets can be addressed by using reliability models. From the maintenance excellence viewpoint, the optimization of asset replacement and resource requirements decisions is essential for continuous improvement [3]. This becomes even more decisive in the case of asset intensive industries -such as mining, aeronautic, defence, or nuclear industries- with high investment equipment to perform operations. The constant pressure to reduce costs and increase utilization often leads to a stress on equipment, affecting reliability and throughput [5]. Hence, the interest lies in improving system reliability. The operation of essential equipment is supported by critical components [6]. Consequently, reliability enhancement of complex equipment can be achieved by preventive replacement of its critical components [3]. Crit-

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Figure C.3: Cover page of **Paper III**. Corresponding author: David R. Godoy Ramos. *Paper under review*

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Critical spare parts ordering decisions using conditional reliability and stochastic lead time

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A B S T R A C T

Asset-intensive companies face great pressure to reduce operation costs and increase utilization. This scenario often leads to over-stress on critical equipment and its spare parts associated, affecting availability, reliability, and system performance. As these resources impact considerably on financial and operational structures, the opportunity is given by demand for decision-making methods for the management of spare parts processes. We proposed an ordering decision-aid technique which uses a measurement of spare performance, based on the stress–strength interference theory; which we have called *Condition-Based Service Level* (CBSL). We focus on *Condition Managed Critical Spares* (CMS), namely, spares which are expensive, highly reliable, with higher lead times, and are not available in store. As a mitigation measure, CMS are under condition monitoring. The aim of the paper is orienting the decision time for CMS ordering or just continuing the operation. The paper presents a graphic technique which considers a rule for decision based on both condition-based reliability function and a stochastic/fixed lead time. For the stochastic lead time case, results show that technique is effective to determine the time when the system operation is reliable and can withstand the lead time variability, satisfying a desired service level. Additionally, for the constant lead time case, the technique helps to define insurance spares. In conclusion, presented ordering decision rule is useful to asset managers for enhancing the operational continuity affected by spare parts.

1. Introduction

Decision-making processes are crucial for organizations within a scenario of intense competitiveness. Since companies are frequently required to reduce production costs and increase asset utilization, misguided decisions may lead to over-stress on equipment. This situation affects reliability and, more importantly, system throughput. Continuous improvement of the ability to add value and enhance profitability of operations is needed by firms in pursuit of performance excellence [1]. An efficient resources ordering is indispensable to achieve significant availability exigencies of equipment-intensive industries, such as mining, aeronautic, nuclear energy, or defence. This equipment is supported by spare parts inventories, which are particularly relevant considering the influence of stock-outs on downtime [2]. Appropriate spare parts allocation decisions are therefore essential to system performance of these industries.

Spare parts play a fundamental role in the support of critical equipment. In a typical company, approximately one third of all assets corresponds to inventories [3]. Of these assets, critical spare parts have special relevance because they are associated with both significant investment and high reliability requirements. As an example, spares inventories sum up above US$ 50 billion in the airlines business [4]. The mismanagement of spare parts that support critical equipment conduces to considerable impacts on financial structure and severe consequences on operational continuity. The improvement of key profits on both logistics and maintenance performance can be achieved by inventory management of costly components, which have extremely criticality on equipment-intensive industries [5]. Therefore, efficient decisions about spare-stocking policies can become essential in the cost structure of companies. In order to provide an efficient spare management performance, a suitable ordering strategy can be relevant. A spare part classification scheme becomes necessary to set optimal policies for those spares that may affect the system the most, and at the least effort. We proposed an ordering decision-aid method to secure the spare management performance into an operational environment that needs continuity to compete into a demanding business context.

1.1. Critical spare parts and maintenance strategy

The need for spare parts inventories is dictated by maintenance actions [6]. In addition, maintenance strategy can be treated by

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Figure C.4: Cover page of **Paper II**. Corresponding author: David R. Godoy Ramos

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Throughput centered prioritization of machines in transfer lines

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ABSTRACT

In an environment of scarce resources and complex production systems, prioritizing is key to confront the challenge of managing physical assets. In the literature, there exist a number of techniques to prioritize maintenance decisions that consider safety, technical and business perspectives. However, the effect of risk mitigating elements—such as intermediate buffers in production lines—on prioritization has not yet been investigated in depth. In this line, the work proposes a user-friendly graphical technique called the *system efficiency influence diagram* (SEID). Asset managers may use SEID to identify machines that have a greater impact on the system throughput, and thus set prioritized maintenance policies and/or redesign of buffers capacities. The tool provides insight to the analyst as it decomposes the influence of a given machine on the system throughput as a product of two elements: (1) system influence efficiency factor and (2) machine unavailability factor. We illustrate its applicability using three case studies: a four-machine transfer line, a vehicle assembly line, and an open-pit mining conveyor system. The results confirm that the machines with greater unavailability factors are not necessarily the most important for the efficiency of the production line, as it is the case when no intermediate buffers exist. As a decision aid tool, SEID emphasizes the need to move from a maintenance vision focused on machine availability, to a systems engineering perspective.

1. Introduction

To meet the increasing challenges of current industrial environment, organizations must continuously enhance their capability to add value and improve the cost-effectiveness of their decision processes. These include the selection of those systems (machines) and actions that may render the highest overall savings with the lowest efforts, and then, set their associated lifecycle policy resolutions. Setting such policies requires resources. As these resources are usually scarce and the number of machines is usually high, a systematic prioritization process must be established [1] and a proper decision aid tool must be selected.

The Pareto analysis has been commonly used to select the components and most critical failure modes of a system. A limitation of this approach is that it uses a single criterion to prioritize. In maintenance management, availability is a typical indicator. This indicator does not allow to ensure whether the cause of failure is a high frequency (reliability) or long downtime (maintainability). To help overcome this problem, Labib [2] suggests the *decision-making grid*. It uses a diagram that includes frequency and downtime, allowing the monitoring of equipment and indicating the appropriate action. An example of a non-graphical technique is the *analytic hierarchy process* which uses pairwise comparisons and relies on the judgements of experts to derive priority scales [3]. A disadvantage of using this method is that in situations with a sizeable number of alternatives, the required comparison step can be unwieldy and excessive resource consuming. In the case of *failure mode and effect analysis* (FMEA), the rating to calculate the priority of the failures is called *risk priority number* [4], *severity* [5] and/or *criticality rank* [6], which is worked out by the product of different ratings: frequency, consequence, detectability, etc. Nonetheless, in many cases the estimation of these factors can be highly subjective. A more advanced technique is proposed by Knights [7] through the *Jack knife diagram* (JKD), a logarithmic scatter plot that involves simultaneously three performance indicators: frequency, downtime, and unavailability. Using JKD, it is possible to classify failures as acute and/or chronic. Acute failures indicate problems in inspections, resource availability, preventive maintenance, among others. Furthermore, chronic failures indicate problems in equipment operation and materials quality. The JKD technique only considers time-based information, excluding economic effects which certainly affect prioritization in a business context. In order to surpass this limitation, Pascual et al. [1] propose the *cost scatter diagram* (CSD) that incorporates the economic

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